Exhibit 58

UNITED STATES DISTRICT COURT
SOUTHERN DISTRICT OF NEW YORK

STATE OF NEW YORK, et al., Plaintiffs, v. DONALD J. TRUMP, *in his official capacity as President of the United States*, et al., Defendants.	20-CV-5770 (JMF)
NEW YORK IMMIGRATION COALITION, et al., Plaintiffs, v. DONALD J. TRUMP, *in his official capacity as President of the United States*, et al., Defendants.	20-CV-5781 (JMF)

EXPERT DECLARATION OF DR. CHRISTOPHER WARSHAW

I. Introduction

1. My name is Christopher Warshaw. I have been an Assistant Professor of Political Science at George Washington University since August 2017. I was recently awarded tenure, and will become a tenured Associate Professor on September 1, 2020. Prior to working at George Washington University, I was an Associate Professor at the Massachusetts Institute of Technology from July 2016 - July 2017, and an Assistant Professor at MIT from July 2012 - July 2016.
2. I have been asked by counsel representing the plaintiffs in *New York Immigration Coalition* v. *Trump* and *State of New York* v. *Trump* to analyze relevant data and provide my expert opinions.
3. More specifically, I have been asked:
    - To forecast the populations of every state in the United States in 2020.
    - To estimate the proportion of the population in every state in the United States likely to be excluded if undocumented immigrants are not included in the Census enumeration used for apportionment.
    - To analyze the likely effects of the exclusion of undocumented immigrants on the apportionment of representatives across states for the U.S House of Representatives.
4. My opinions are based on the knowledge I have amassed over my education, training and experience, including a detailed review of the relevant academic literature. They also follow from a statistical analysis that I describe in detail below.

A. Qualifications and Publications

5. My Ph.D. is in Political Science, from Stanford University, where my graduate training included courses in political science and statistics. I also have a J.D. from Stanford Law School. My academic research and teaching focuses on public opinion based on surveys and Census data, as well as the study of representation, elections, and polarization in American Politics. I have also taught courses on statistical analysis.

6. My *curriculum vitae* is attached to this Declaration at Appendix C. All publications that I have authored and published appear in my *curriculum vitae*. I have published 30 academic articles and book chapters. My work is published or forthcoming in peer-reviewed journals such as: the *American Political Science Review*, the *American Journal of Political Science*, the *Journal of Politics*, *Political Analysis*, *Political Science Research and Methods*, the *British Journal of Political Science*, *Political Behavior*, the *Annual Review of Political Science*, the *Election Law Journal*, *Nature Energy*, *Public Choice*, and edited volumes from Cambridge University Press and Oxford University Press. My non-academic writing has been published in the *New York Times* and the *Washington Post*.

7. Most relevantly, I provided an expert report and declaration in *New York Immigration Coalition et al* v. *United States Department of Commerce*, No. 18-CV-2921-JMF (S.D. NY). In that report, I assessed the consequences of an undercount caused by a potential citizenship question on the U.S. Census. Specifically, I examined the effects of a net differential undercount of people who live in immigrant households on congressional apportionment. I found that the inclusion of a citizenship question on the Census would likely have led to substantial effects on the population counts of each state, and the apportionment of

representatives across states for the U.S House of Representatives. In that case, the court found my analysis and findings "credible and persuasive."

8. I have also previously provided expert reports in *League of Women Voters of Pennsylvania* v. *Commonwealth of Pennsylvania*, No. 159 MM 2017 (PA 2018); *League of Women Voters of Michigan* v. *Johnson*, No. 2:17-cv-14148 (E.D. 2019); and *PRI et al* v. *Smith et al.,* No. 18-cv-357 (S.D. Ohio 2018).

9. The opinions in this declaration are my own, and do not represent the views of George Washington University.

B. Research Design

10. President Trump recently issued a presidential memorandum charging the Secretary of Commerce to "exclude from the apportionment base aliens who are not in a lawful immigration status under the Immigration and Nationality Act."[1] In order to assess the consequences of excluding undocumented immigrants from the count of people in the United States used for apportionment, I conduct the following steps:

    A. I estimate the baseline population of each state in 2020 based on the Census Bureau's annual estimates of the population of each state from the past three decades.[2] The populations used for apportionment also include overseas federal employees and their dependents. Then, based on data from the U.S. Military and the Census Bureau, I

[1] See https://www.whitehouse.gov/presidential-actions/memorandum-excluding-illegal- aliens-apportionment-base-following-2020-census/.

[2] For the state populations from 2010-2019, I used the file 'nst-est2019-01.xlsx' which I obtained from https://www.census.gov/newsroom/press-kits/2019/national-state-estimates.html. For the populations from 2000-2009, I used the file 'st-est00int-01.xls' from https://www.census.gov/data/ tables/time-series/demo/popest/intercensal-2000-2010-state.html. For the population counts from 1990-1999, I used the data available at https://www.census.gov/data/tables/time-series/ demo/popest/intercensal-1990-2000-state-and-county-totals.html.

estimate the number of overseas federal employees and dependents that would be added to the population of each state for apportionment.

B. I use data from the Pew Research Center to estimate the number of undocumented immigrants in each state in 2020. These are the most widely used data in the academic literature on the undocumented immigrant population. However, I reach very similar conclusions using a variety of alternative sources of data on the number of undocumented immigrants in each state.

C. Based on all of these data, I estimate the proportion of each state's population that would be excluded from the enumeration used for apportionment due to the presidential memorandum. I then use the official apportionment table published by the U.S. Census Bureau to estimate the number of congressional seats that states would gain or lose. Finally, I report the uncertainty in all of my analyses.

D. I evaluate the robustness of my findings to a variety of alternative data sources and modeling strategies. I also compare my findings to four other independent reports from different research groups. My findings are robust to alternative modeling assumptions and are similar to these other groups' findings.

C. Summary of Findings

11. Based on my analysis, I have reached the following conclusions:

- The exclusion of undocumented immigrants from the apportionment base (i.e., the population enumeration used for apportionment) is likely to have substantial effects on the population counts of each state, and the apportionment of representatives across states for the U.S House of Representatives.

- It will almost certainly lead Texas to lose a seat in Congress. It is likely to lead California and New Jersey to lose a congressional seat. It also could lead other states, such as Arizona, Florida, New York, or Illinois, to lose seats. These conclusions are similar across multiple data sources on the prevalence of undocumented immigrants. They are also similar to the conclusions reached by a variety of independent analysts and organizations.
- The exclusion of undocumented immigrants from the apportionment base would affect political representation in Congress. For instance, it is likely to affect the distribution of federal funds to each state, and the general power that each state holds in Congress.

II. Projecting the State Populations in 2020

12. The first stage of my analysis is to develop baseline projections of the population of each state in the country in 2020. These projections are critical to determining the likely effects of excluding undocumented immigrants from the apportionment base. In order to develop these estimates, I use the Census Bureau's official estimates of the population of each state from 1990-2019. The Census Bureau does not provide public estimates of each geographic unit's populations in future years.

13. In this section, I first discuss several possible approaches for estimating future populations. I show that my preferred approach performs as well or better at a similar modeling problem than alternative approaches. I then discuss how I incorporate uncertainty into my population projections. Finally, I present estimates of the 2020 populations in each state in the country.

A. Data

14. The Census Bureau's Population Estimates Program (PEP) produces estimates of the population for the United States, states, counties, cities, towns, and other geographic areas.

These aggregate estimates are based on the demographic components of population change (births, deaths, and migration) at each level of geography.[3] My population projections are based on these official population estimates for each state for the period from 1990-2019.[4]

B. Statistical Model for Population Projections

15. There are a number of potential options for forecasting the likely population of each state in 2020. One possible forecasting option would be to allow the forecasts to increase or decrease over time, where the amount of change over time (called the drift) is set to be the average change in the historical data (see Hyndman and Athanasopoulos 2018, 48-49). Some related methods in this family of forecasting approaches are:

- <u>Model 1: Linear trend between 2010-2019</u>: One approach would be to project forward based on the linear trend in the population estimates since the last Census (e.g., Election Data Services 2017). This approach assumes that each geographic unit's population follows the same linear rate of change in the future that it has followed over the past decade. This approach has the benefit of using many years of data, but it could yield biased estimates if the population trends have changed over this period. I estimate linear trends using a simple linear regression model in the software program R.
- <u>Model 2: Linear trend between 2016-2019</u>: Another possibility is to project forward based on the linear trend in the population estimates over the past 4 years. This approach

[3] I do not directly use the more detailed cohort-component method used by the Census for my population projections because this information is unavailable for some geographic levels, particularly for the 2000-2010 period. It is also unclear whether the additional complexities associated with this approach would yield substantial gains in predictive accuracy.
[4] For the state populations from 2010-2019, I used the file 'nst-est2019-01.xlsx' which I obtained from https://www.census.gov/newsroom/press-kits/2019/national-state-estimates.html. For the populations from 2000-2009, I used the file 'st-est00int-01.xls' from https://www.census.gov/data/ tables/time-series/demo/popest/intercensal-2000-2010-state.html. For the population counts from 1990-1999, I used the data available at https://www.census.gov/data/tables/time-series/ demo/popest/intercensal-1990-2000-state-and-county-totals.html.

assumes that each geographic unit's population follows the same linear trend in the future that it has followed over this shorter time period. This approach has the benefit of being sensitive to more recent trends, but it could be noisier than estimates based on the longer time series. That is, it could be overly sensitive to short-term trends. I estimate linear trends using a simple linear regression model in R.

- Model 3: Change between two most recent years (i.e., 2018 to 2019): A third possibility is to focus on the change between each geographic unit's populations in the two most recent years and assume that future years will follow this recent trend. This approach has the benefit of being based on the most recent changes in populations, but it could also be overly sensitive to short-term idiosyncratic trends. I estimate these short-term trends using the software program R.

16. As Hyndman and Athanasopoulos (2018, 50) discusses: "Sometimes one of these simple methods will be the best forecasting method available; but in many cases, these methods will serve as benchmarks rather than the method of choice. That is, any forecasting methods [] will be compared to these simple methods to ensure that the new method is better than these simple alternatives. If not, the new method is not worth considering." I consider one more complex approach against these benchmarks:

- Model 4: A state space model with exponential smoothing: This approach uses an exponential smoothing model that weights levels and trends to an extent determined by the data (Hyndman et al. 2008; Hyndman and Athanasopoulos 2018). This model uses all of the available data, but it gives more weight to the most recent years. I estimate the exponential smoothing model using the ets function in the forecast package in R.

C. Validation of Population Projections

17. The accuracy of forecasting models can only be determined by considering how well a given model performs on new data that were not used when fitting the original model (Hyndman and Athanasopoulos 2018, 62). In order to choose the best model for this analysis, I evaluated each model using a benchmark that is similar to the challenge of forecasting the 2020 populations. Specifically, I forecasted the 2019 population estimates in each state based on 1990-2018 population data. For each analysis I used the following evaluation metrics (see Hyndman and Athanasopoulos 2018, 64-65).

- <u>The mean error across states (ME)</u>: This helps assess whether a given metric has a systematic bias in one direction or another.
- <u>The root mean-squared error across states (RMSE)</u>: This helps assess the accuracy of the forecasts. It penalizes larger errors more than smaller errors.
- <u>The mean absolute error across states (MAE)</u>: This helps assess the accuracy of the forecasts. It penalizes all errors equally.
- <u>The mean percentage error across states (MPE)</u>: This helps assess whether a given metric has a systematic bias in one direction or another. It has the advantage of being unit-free (i.e., the interpretation is similar in small and large states).
- <u>The mean absolute percentage error across states (MAPE)</u>: This metric also helps assess the accuracy of the forecasts. It has the advantage of being unit-free (i.e., the interpretation is similar in small and large states).

Table 1: Validation of State Population Projections at Predicting 2019 State Populations

	Model	ME	RMSE	MAE	MPE	MAPE
(1):	Linear model (decade)	-20,821	71,748	32,448	-0.29%	0.57%
(2):	Linear model (4 years	-12,219	33,933	14,513	-0.11%	0.21%
(3):	Delta in last two years	-2,940	12,129	6,073	-0.02%	0.09%
(4):	State space model	-4,034	12,623	6,766	-0.04%	0.13%

18. Table 1 shows the results. Overall, the state space model (4) and delta model (3) perform the best in this validation exercise. These models have much less error than the other models across all the metrics. Other studies have shown that state space models generally outperform other modeling approaches due to its flexibility (Hyndman et al. 2008; Hyndman and Athanasopoulos 2018). It also provides measures of uncertainty. As a result, I use this approach in my main analysis. I also show below, however, that I reach very similar findings using the delta model (3) (see Additional Scenario #6).

D. Baseline estimates of 2020 populations

19. The next stage is to use the official Census population estimates to project each geographic unit's population in 2020. Table 2 shows the results.[5] Note that all of the analysis of apportionment that follow fully incorporate the uncertainties in these projections.

[5] The projections shown here do not include the overseas military population, federal employees, and dependents. However, the apportionment projections in Table 6 do include these groups.

Table 2: State population projections

State	2010 Population	2019 Population	2020 Population Projection
Alabama	4,779,736	4,903,185	4,918,700
Alaska	710,231	731,545	728,000
Arizona	6,392,017	7,278,717	7,399,400
Arkansas	2,915,918	3,017,804	3,025,900
California	37,253,956	39,512,223	39,724,500
Colorado	5,029,196	5,758,736	5,833,000
Connecticut	3,574,097	3,565,287	3,565,300
Delaware	897,934	973,764	982,000
District of Columbia	601,723	705,749	710,000
Florida	18,801,310	21,477,737	21,706,500
Georgia	9,687,653	10,617,423	10,723,200
Hawaii	1,360,301	1,415,872	1,411,500
Idaho	1,567,582	1,787,065	1,823,600
Illinois	12,830,632	12,671,821	12,622,100
Indiana	6,483,802	6,732,219	6,769,900
Iowa	3,046,355	3,155,070	3,168,400
Kansas	2,853,118	2,913,314	2,915,500
Kentucky	4,339,367	4,467,673	4,474,200
Louisiana	4,533,372	4,648,794	4,650,500
Maine	1,328,361	1,344,212	1,349,400
Maryland	5,773,552	6,045,680	6,071,200
Massachusetts	6,547,629	6,892,503	6,904,900
Michigan	9,883,640	9,986,857	9,986,900
Minnesota	5,303,925	5,639,632	5,676,100
Mississippi	2,967,297	2,976,149	2,972,300
Missouri	5,988,927	6,137,428	6,152,400
Montana	989,415	1,068,778	1,077,400
Nebraska	1,826,341	1,934,408	1,946,500
Nevada	2,700,551	3,080,156	3,132,200
New Hampshire	1,316,470	1,359,711	1,363,300
New Jersey	8,791,894	8,882,190	8,894,300
New Mexico	2,059,179	2,096,829	2,100,400
New York	19,378,102	19,453,561	19,377,200
North Carolina	9,535,483	10,488,084	10,594,600
North Dakota	672,591	762,062	766,100
Ohio	11,536,504	11,689,100	11,706,400
Oklahoma	3,751,351	3,956,971	3,971,200
Oregon	3,831,074	4,217,737	4,260,000
Pennsylvania	12,702,379	12,801,989	12,803,100
Rhode Island	1,052,567	1,059,361	1,059,400
South Carolina	4,625,364	5,148,714	5,213,000
South Dakota	814,180	884,659	891,700
Tennessee	6,346,105	6,829,174	6,886,700
Texas	25,145,561	28,995,881	29,432,600
Utah	2,763,885	3,205,958	3,259,800
Vermont	625,741	623,989	624,100
Virginia	8,001,024	8,535,519	8,570,600
Washington	6,724,540	7,614,893	7,707,400
West Virginia	1,852,994	1,792,147	1,780,000
Wisconsin	5,686,986	5,822,434	5,836,800
Wyoming	563,626	578,759	578,700

III. Estimating the Overseas Federal Population Allocated to each State

20. The population estimates above include all people living in the United States. However, the populations used for apportionment also include overseas federal employees and their

dependents.[6] Thus, it is necessary to estimate how overseas federal employees and dependents would be allocated for purposes of apportionment.

21. In the 2010 Census, the overseas military population were generally allocated to their "home of record" (the address provided when the service member entered the military) for purposes of apportionment.[7] For the 2020 Census, however, all overseas federal personnel will be counted at their usual residential address in the United States.[8] In other words, military personnel will typically be counted as residing in or near the domestic base where they are stationed. Unfortunately, there is no currently available public estimate of how these overseas personnel will be allocated to individual states. The Census Bureau has stated that it plans to count federal personnel living outside the United States, and their dependents living with them outside the United States, using administrative data provided by the Department of Defense and the Department of Homeland Security.[9]

22. I used the following process to estimate the number of overseas federal population that will be allocated to each state for apportionment:

- First, I estimated the number of military personnel overseas in each branch using data from the Department of Defense from March, 2020.[10]
- Second, I allocated these personnel to each state in proportion to the number of service members in each branch based in each state.[11] This approach implicitly assumes that each

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[6] "Overseas" is defined as anywhere outside the 50 U.S. States and the District of Columbia.
[7] See the Census Bureau's FAQ on Congressional Apportionment in the 2010 Census. https://webcache.googleusercontent.com/search?q=cache:WTXwriFql5AJ:https://www.census.gov/population/apportionment/about/faq.html+&cd=2&hl=en&ct=clnk&gl=us&client=safari and https://www.prb.org/how-does-the-u-s-census-bureau-count-people-who-have-more-than- one-address/.
[8] See https://www.prb.org/how-does-the-u-s-census-bureau-count-people-who-have-more- than-one-address/.
[9] See https://www.doi.gov/sites/doi.gov/files/uploads/oia-02052020-census-and-the- military.pdf.
[10] I used the spreadsheet DMDC_Website_Location_Report_2003.xlsx that is available from https: //www.dmdc.osd.mil/appj/dwp/dwp_reports.jsp.

member of the military has an equal probability of being assigned abroad. While this is clearly a simplification, I believe it is the most reasonable analytical approach with currently available data.

- Third, I assumed that military personnel have the same number of dependents (1.44) as they did in the 2010 Census.[12]
- Finally, I assumed that the overseas federal civilian population is the same as in 2010 (39,674). Since the majority of overseas federal civilian employees are with the State Department,[13] I assume these are all headquarters staff that work in Washington DC. I use ACS Commuting Flows from the Census to allocate them between the District of Columbia, Virginia, and Maryland.[14] I also assumed that these civilian employees each have 1.44 dependents.
- Of course, this estimation method has considerable uncertainty. So I assumed that there is a standard error associated with my estimates of the overseas federal population for each state that is equal to 10% of the size of the estimates.

23. Based on this methodology, I estimate that there are about 230,000 overseas federal personnel. Including dependents, I estimate there are about 561,000 federal employees and dependents overseas population will be included for purposes of apportionment for the 2020 Census. Table 3 shows the state-by-state results. A copy of Table 3 is provided in Appendix

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[11] I used the spreadsheet DMDC_Website_Location_Report_2003.xlsx that is available from https: //www.dmdc.osd.mil/appj/dwp/dwp_reports.jsp.

[12] I used the "2010 Census Federally Affiliated Overseas Count Operation Assessment Report" that is available at https://www.census.gov/2010census/pdf/2010_Census_Federally_Affiliated_ Overseas_Count_Operation_Assessment.pdf.

[13] See the '2010 Census Federally Affiliated Overseas Count Operation Assessment Report' that is available at https://www.census.gov/2010census/pdf/2010_Census_Federally_Affiliated_Overseas_ Count_Operation_Assessment.pdf.

[14] 98% of people that work in Washington DC live in Maryland, Virginia, or Washington, DC. See https://www.census.gov/data/tables/2015/demo/metro-micro/commuting-flows-2015.html.

A to this Declaration. My estimates indicate that California, North Carolina, Texas, and Virginia have the largest overseas federal populations.[15] It is important to note that the federal overseas population is down by nearly 50% since the 2010 Census.[16] This likely reflects the reduction in the nation's military deployments in conflict areas over the past decade.[17]

IV. Estimating the Number of Undocumented Immigrants in Each State

24. The President's Memorandum charges the Secretary of Commerce to "exclude from the apportionment base aliens who are not in a lawful immigration status under the Immigration and Nationality Act."[18] In order to assess the impact of this memorandum, we next need to estimate the number of undocumented immigrants in each state.

25. There is no official estimate from the Census Bureau or any other federal government agency of the number of undocumented immigrants in each state that would be affected by the President's memorandum. The most commonly used estimates of the number of undocumented people have been developed by the Pew Research Center.[19] There are hundreds of citations in Google Scholar for Pew's estimates of the number of undocumented immigrants in the United States. As a result, I use these estimates in my main analysis. However later, I also examine the estimates of the number of undocumented immigrants from a number of other organizations that use a variety of slightly different methodologies.

[15] These estimates seem to be in-line with discussions in news coverage of apportionment. See https://www.rollcall.com/2020/02/26/census-troop-counting-rules-could-tip- congressional-balance/.
[16] I use information on these populations from the 2010 apportionment available at https://www. census.gov/data/tables/2010/dec/2010-apportionment-data.html.
[17] See Pew's report on the number of overseas military personnel at https://www.pewresearch.org/ fact-tank/2017/08/22/u-s-active-duty-military-presence-overseas-is-at-its-smallest- in-decades/.
[18] See https://www.whitehouse.gov/presidential-actions/memorandum-excluding-illegal- aliens-apportionment-base-following-2020-census/.
[19] See https://www.pewresearch.org/fact-tank/2019/06/12/us-unauthorized-immigrant- population-2017/.

Each of these analyses yields substantively similar conclusion as my main analysis using Pew's data.

26. Pew estimates the U.S. unauthorized immigrant population from 1995-2017 in each state based on a residual estimation methodology that compares a demographic estimate of the number of immigrants residing legally in the country with the total number of immigrants as measured by either the American Community Survey (ACS) or the March Supplement to the Current Population Survey (CPS).[20] The difference is assumed to be the number of unauthorized immigrants in the survey, a number that later is adjusted for omissions from the survey (see below). The basic estimate is:

$$\text{Unauthorized Immigrants (U)} = \text{Survey, Total Foreign Born (F)} - \text{Estimated Lawful Immigrant Population (L)}$$

27. The lawful resident immigrant population was estimated by applying demographic methods to counts of lawful admissions covering the period since 1980 obtained from the Department of Homeland Security's Office of Immigration Statistics[21] and its predecessor at the Immigration and Naturalization Service, with projections to current years, when necessary. Initial estimates were calculated separately for age-gender groups in six states (California, Florida, Illinois, New Jersey, New York and Texas) and the balance of the country. This residual method has been used in a wide variety of government reports and peer reviewed articles (e.g., Baker 2018; Warren and Warren 2013; Passel 2016).

28. The overall estimates for unauthorized immigrants built on these residuals by adjusting for survey omissions in these six states and the balance of the country, subdivided for Mexican immigrants and other groups of immigrants (balance of Latin America, South and East Asia,

[20] The next few paragraphs of this section are adapted from Pew's discussion of their methodology at https://www.pewresearch.org/hispanic/2018/11/27/unauthorized-immigration- estimate-methodology/.
[21] See https://www.dhs.gov/immigration-statistics/yearbook/2016/.

rest of world) depending on sample size and state. Once the residual estimates were produced, Pew assigned individual foreign-born respondents in the survey a specific status (one option being unauthorized immigrant) based on the individual's demographic, social, economic, geographic and family characteristics in numbers that agree with the initial residual estimates for the estimated lawful immigrant and unauthorized immigrant populations in the survey. A last step in the weighting-estimation process involves developing state-level estimates that take into account trends over time in the estimates.

29. Overall, Pew estimates there were about 10,481,000 undocumented immigrants in the United States in 2017.[22] They estimate that the states with the most undocumented immigrants are California, Texas, Florida, New York, and New Jersey. The states with the fewest undocumented immigrants are Maine, Montana, Vermont, and West Virginia.

30. Of course, Pew's estimation process has substantial uncertainties inherent in it. First, there is no way to know that individual respondents to the ACS and CPS are undocumented immigrants. Pew estimates undocumented status based on a variety of pieces of information.[23] Second, the ACS and CPS are themselves surveys, subject to sampling error. There could also be misreporting of country of birth on the ACS and/or unit non response by undocumented immigrants (Brown et al. 2018). In order to characterize these uncertainties, Pew provides a 90% confidence interval for their estimates of the number of undocumented people in each state.

[22] These estimates seem plausible since the Department of Homeland Security estimated there were 12 million undocumented immigrants in the country in January 2015 (Baker 2018). They are also similar to estimates of the number of undocumented immigrants developed by other think tanks (see below).
[23] See https://www.pewresearch.org/hispanic/2018/11/27/unauthorized-immigration- estimate-methodology/.

31. Lastly, Pew's data of the number of undocumented immigrants in each state between 1995-2017 need to be projected 3 years forward to 2020.[24] To determine how to forecast the number of undocumented immigrants in each state, I compared the same four modeling strategies that I discussed earlier for the state population projections. For each method, I used data through 2014 to evaluate its performance at predicting the number of undocumented immigrants three years forward in 2017.

32. All of the models generate significant levels of error compared to the population forecasting validation shown above in Table 4. However, the state space model (4) and a linear time trend (2) using the previous four years of data perform somewhat better than the other models. In my main analysis, I use the state space model to project the number of undocumented immigrants in 2020. Moreover, I ensured that the state space model estimates fully incorporate the uncertainty in Pew's estimates in the number of undocumented immigrants (see Treier and Jackman 2008; Caughey and Warshaw 2018).[25] I checked the robustness of my analysis by showing that I reach similar substantive conclusions using the linear time trend model (see Additional Scenario #7).

Table 4: Validation of Forecasting Pew's Estimates of the Number of Undocumented Immigrants in 2017

	Model	ME	RMSE	MAE	MPE	MAPE
(1):	Linear model (decade)	-21,998.25	90,634.40	31,639.51	-3.34	14.56
(2):	Linear model (4 years)	-10,944.23	50,403.96	25,971.15	-3.95	17.59
(3):	Delta in last two years	-12,884.62	58,005.64	28,961.54	-0.40	19.24
(4):	State space model	-13,688.05	55,204.49	22,794.32	-3.46	15.48

[24] Pew's data are available at https://www.pewresearch.org/hispanic/interactives/ unauthorized-trends/.
[25] Specifically, I used the following approach. First, I constructed 100 simulations of the number of undocumented immigrants in each state from 2005-2017 using Pew's estimates and the associated confidence intervals. For each simulation, I used the state space model to forecast each state's number of undocumented immigrants in 2020. I then constructed a bootstrap sample of the forecast of undocumented immigrants in each state based on the mean and confidence intervals in the state space model's population forecast. Finally, I estimated the number of undocumented immigrants in each state in 2020, and its associated standard error to represent uncertainty, based on these simulations.

33. Table 5 shows the estimates of the number of undocumented immigrants in each state (standard errors that represent uncertainty are in parentheses). A copy of Table 5 is provided in Appendix A to this Declaration. Its shows that California, Florida, Illinois, New Jersey, New York, and Texas each have at least 400,000 undocumented immigrants.[26]

34. These final estimates take into account the uncertainty in Pew's initial estimates of the number of undocumented immigrants from 2005-2017. They also take into account the uncertainty in projecting the trends in each state from 2017-2020. In general, the additional uncertainty associated with forecasting to 2020 approximately triples the size of Pew's confidence intervals for their estimates of undocumented immigrants in each state in 2017.

A. Incorporating Uncertainty

35. All modeled estimates have uncertainty. My analyses uses bootstrap simulations to incorporate three sources of uncertainty in all my models:

- The uncertainty in the population forecasts in every state for 2020.
- The uncertainty in the estimates of the overseas federal employees and dependents, and how they are allocated to states.
- The uncertainty in the estimate of the number of undocumented immigrants in each state in 2020.

V. State-level Effects of Excluding Undocumented Immigrants from Apportionment Base

36. Now that we have calculated population projections and estimates of the number of undocumented immigrants in each state, we are in a position to estimate state-level impacts.

[26] These state-by-state figures are similar to those in a 2015 Department of Homeland Security report, which provided estimates of the number of undocumented immigrants in several states (Baker 2018).

A. Effect on State Population Enumerations

37. To begin, I analyzed the effects on the enumerated population of each state in 2020. The results are shown in Table 6. Column (1) of Table 6 shows the baseline apportionment population projections for each state (including the overseas military population, federal employees, and dependents). Column (2) shows my estimate of the number of undocumented immigrants in each state in 2020. Column (3) shows my estimate of the percentage of the apportionment population in each state that consists of undocumented immigrants.

Table 6: Estimates of Effect on State Population Enumerations in 2020

State	Baseline 2020 Apportionment Population	Undocumented Immigrants (Pew)	Undocumented Percentage
	(1)	(2)	(3)
Alabama	4,926,400	71,900	1.5%
Alaska	735,700	8,400	1.1%
Arizona	7,410,500	274,400	3.7%
Arkansas	3,028,800	65,300	2.2%
California	39,799,200	2,066,000	5.2%
Colorado	5,846,100	190,100	3.3%
Connecticut	3,568,100	148,300	4.2%
Delaware	984,300	29,700	3%
Florida	21,736,600	796,000	3.7%
Georgia	10,749,300	375,700	3.5%
Hawaii	1,428,900	43,800	3.1%
Idaho	1,825,700	38,300	2.1%
Illinois	12,633,400	409,300	3.2%
Indiana	6,773,300	103,200	1.5%
Iowa	3,169,100	51,000	1.6%
Kansas	2,924,300	81,300	2.8%
Kentucky	4,485,300	44,700	1%
Louisiana	4,657,900	100,100	2.1%
Maine	1,350,400	4,000	0.3%
Maryland	6,105,000	261,600	4.3%
Massachusetts	6,907,400	231,900	3.4%
Michigan	9,989,700	103,800	1%
Minnesota	5,677,700	86,800	1.5%
Mississippi	2,979,500	23,000	0.8%
Missouri	6,160,800	63,100	1%
Montana	1,079,300	4,400	0.4%
Nebraska	1,950,200	55,800	2.9%
Nevada	3,137,300	211,200	6.7%
New Hampshire	1,363,700	10,400	0.8%
New Jersey	8,899,400	493,200	5.5%
New Mexico	2,107,400	59,200	2.8%
New York	19,386,100	679,800	3.5%
North Carolina	10,639,700	330,800	3.1%
North Dakota	770,300	5,900	0.8%
Ohio	11,715,100	94,400	0.8%
Oklahoma	3,981,800	90,100	2.3%
Oregon	4,261,500	109,100	2.6%
Pennsylvania	12,809,600	217,800	1.7%
Rhode Island	1,061,000	32,900	3.1%
South Carolina	5,229,800	101,500	1.9%
South Dakota	893,800	5,700	0.6%
Tennessee	6,888,900	139,200	2%
Texas	29,479,700	1,649,100	5.6%
Utah	3,263,900	106,100	3.3%
Vermont	624,400	3,500	0.6%
Virginia	8,639,600	297,600	3.4%
Washington	7,730,300	274,400	3.5%
West Virginia	1,780,600	4,300	0.2%
Wisconsin	5,838,300	72,900	1.2%
Wyoming	580,300	4,800	0.8%

38. Overall, Table 6 indicates that each state would be affected by an exclusion of undocumented immigrants. Figure 1 shows a map of the percentage of people in each state that would be dropped from the Census apportionment base if undocumented immigrants are excluded.

Arizona, California, Colorado, Connecticut, Florida, Georgia, Hawaii, Mary land, Massachusetts, Nevada, New Jersey, New York, North Carolina, Rhode Island, Texas, Utah, Virginia, and Washington would all lose at least 3% of their population from their apportionment base. Thus, they could be at risk of losing a congressional seat during apportionment.

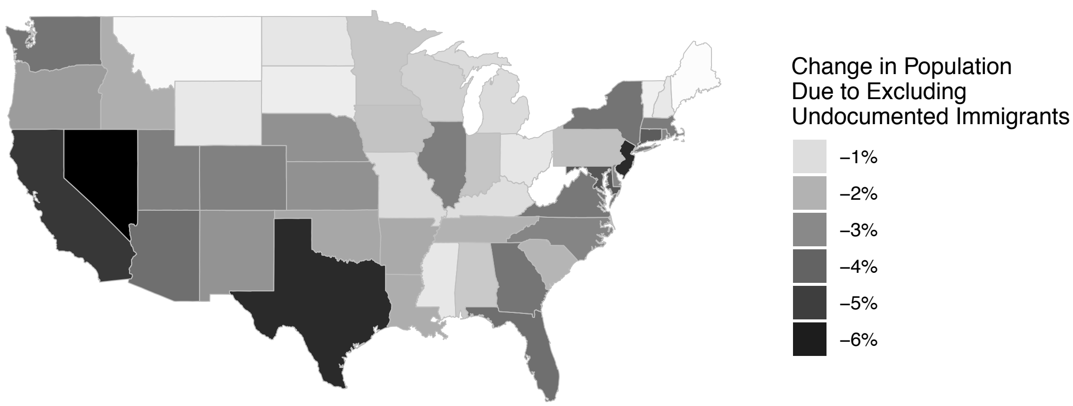

Figure 1: Effects on State Populations

B. Effect on Apportionment

39. Next, I used the population projections and estimates of undocumented immigrants in each state to examine the likely effect of excluding undocumented immigrants from the Census count on the apportionment of seats in the House of Representatives. Article 1, Section 2, of the United States Constitution states: "Representatives and direct Taxes shall be apportioned among the several States which may be included within this Union, according to their respective Numbers."

40. Since the first census in 1790, five methods of apportionment have been used. The government currently uses a method called the Method of Equal Proportions, which was

adopted by Congress in 1941 following the census of 1940. This method first assigns each state one seat. Then, additional seats in the House of Representatives are assigned to a "priority" value. The priority value for each seat is determined by multiplying the population of a state by a "multiplier." The multiplier is $1/\sqrt{n(n-1)}$. So the formula for calculating the multiplier for the second seat is $1/\sqrt{2(2-1)}$ or 0.70710678, the formula for calculating the multiplier for the third seat is $1/\sqrt{3(3-1)}$ or 0.40824829, and so on. The Census provides an official table of these multipliers, which I used for my calculations.[27]

41. The next step is to multiply the multipliers by the population total for each of the 50 states (the District of Columbia is not included in these calculations). The resulting numbers are the priority values. Multipliers and priority values must be calculated for the largest number of seats that could be assigned to a state. In my analysis, I calculated the priority values for each state for seats 2 through 60. The next step is to rank and number the resulting priority values starting with seat 51 until all 435 seats have been assigned. The final step is to tally the number of seats for each state to arrive at the total number of seats in the House of Representatives apportioned to each state.

42. I conducted these steps for 1,000 simulations of the population projections and undocumented populations in each state. Table 7 shows the results.[28] Column (1) shows the rounded, baseline projections for the number of seats that each state is likely to receive in 2020 if there is a full population enumeration. Column (2) shows the rounded projections for the number of seats that each state is likely to receive in 2020 if undocumented immigrants are excluded from the apportionment base. Column (3) shows the rounded, average change in

[27] See https://www.census.gov/population/apportionment/about/computing.html.
[28] Table 12 in the Appendix A shows unrounded numbers for this table.

the number of congressional seats each state would gain or lose due to the exclusion of undocumented immigrants. Finally, column (4) shows the probability that each state would lose at least one seat.

Table 7: Estimates of Effect of Excluding Undocumented Immigrants on Congressional Apportionment

State	Baseline Seats (1)	Seats after Exclusion (2)	Seat Delta (3)	Prob. Seat Loss (4)
Alabama	6	7	1	0%
Alaska	1	1	0	0%
Arizona	10	10	-0	0.3%
Arkansas	4	4	0	0%
California	52	51	-1	72.1%
Colorado	8	8	-0	0.3%
Connecticut	5	5	-0	3.4%
Delaware	1	1	0	0%
Florida	29	28	-0	38.4%
Georgia	14	14	0	0%
Hawaii	2	2	0	0%
Idaho	2	2	0	0%
Illinois	17	17	-0	10.1%
Indiana	9	9	0	0%
Iowa	4	4	0	0%
Kansas	4	4	0	0%
Kentucky	6	6	0	0%
Louisiana	6	6	0	0%
Maine	2	2	0	0%
Maryland	8	8	0	0%
Massachusetts	9	9	0	0%
Michigan	13	13	0	0%
Minnesota	7	8	1	0%
Mississippi	4	4	0	0%
Missouri	8	8	0	0%
Montana	2	2	0	0%
Nebraska	3	3	0	0%
Nevada	4	4	0	0%
New Hampshire	2	2	0	0%
New Jersey	12	11	-1	69.8%
New Mexico	3	3	0	0%
New York	26	25	-0	18.9%
North Carolina	14	14	0	0%
North Dakota	1	1	0	0%
Ohio	15	16	1	0%
Oklahoma	5	5	0	0%
Oregon	6	6	0	0%
Pennsylvania	17	17	0	0%
Rhode Island	1	1	0	0%
South Carolina	7	7	0	0%
South Dakota	1	1	0	0%
Tennessee	9	9	0	0%
Texas	39	38	-1	98.3%
Utah	4	4	0	0%
Vermont	1	1	0	0%
Virginia	11	11	0	0%
Washington	10	10	0	0%
West Virginia	2	2	0	0%
Wisconsin	8	8	0	0%
Wyoming	1	1	0	0%

43. My analysis indicates that there is a 98% chance that Texas would lose a Congressional seat if undocumented immigrants are excluded from the apportionment base. It loses a seat in

nearly every single one of my simulations. In addition, my analysis indicates that there is a 72% chance that California would lose a Congressional seat. On average, it loses .83 seats across my simulations (i.e., in most simulations it loses 1 seat, in some it loses 2 seats, and in some it loses zero seats). My analysis also indicates that there is a 70% chance that New Jersey would lose a Congressional seat if undocumented immigrants are excluded from the apportionment base. There are smaller chances that several other states could lose seats, including Connecticut, Florida, Illinois, and New York.[29]

44. The states that lose seats in Congress would likely see decreases in their share of federal outlays due to their reduction in voting power in Congress. A number of economics and political science studies have found that distributive spending is allocated in part based on the number of seats that a geographic area has in Congress (e.g., Ansolabehere, Gerber, and Snyder 2002; Cascio and Washington 2014; Elis, Malhotra, and Meredith 2009). For instance, Elis, Malhotra, and Meredith (2009) find that a 10% increase in a state's share of the U.S. House of Representatives equates to a 0.7% increase in a state's share of the federal budget. This implies that an extra congressional seat can gain a state as much as $100 per capita in additional federal funding (360).

VI. Robustness Checks

45. It is always helpful to evaluate the robustness of any analysis to alternative modeling assumptions. In this section, I undertake four different robustness checks. First, I evaluate the impact of using alternative sources of information on the number of undocumented immigrants in each state on my analysis. Second, I evaluate the impact of alternative population forecasting methodologies. Third, I evaluate whether my conclusions would differ

[29] Note the rounded numbers in Table 7 imply that Florida and New York would lose seats. The unrounded numbers in the Appendix (Table 12), however, show that there is a less 50% chance that they would lose a seat.

if former Census Director John H. Thompson is correct that the exclusion of undocumented immigrants from the apportionment base would cause an undercount of immigrant populations. I used the foreign-born population in the United States to evaluate the impact of an undercount of immigrants. Fourth, I compare my results to the conclusions of various organizations' reports on the impact of excluding undocumented immigrants on apportionment.

46. Overall, the analysis in this section shows that my conclusions are robust to a wide variety of alternative data sources and modeling strategies. They are also consistent with the findings of other organizations and analysts. All of these alternative data sources, methodologies, and third-party reports indicate that Texas would lose a congressional seat if undocumented immigrants are excluded from the apportionment base. They nearly all indicate that California would lose a seat. They also indicate that some mix of Florida, New Jersey, and New York could lose seats.

A. Robustness to Alternative Estimates of the Number of Un documented Immigrants

47. Due to the substantial uncertainties in Pew's estimates of the number of undocumented people in each state, I conducted a canvass of alternative sources of estimates for the undocumented population. I identified several alternative sources of data:

- Additional Scenario 1: The Migration Policy Institution (MPI) has developed estimates of the number of undocumented people in each state based on the U.S. Census Bureau's 2012-16 American Community Survey data.[30] They estimate there are about 11,300,000 undocumented immigrants in the United States. Their national estimate is very similar to

[30] See https://www.migrationpolicy.org/programs/us-immigration-policy-program-data-hub/unauthorized-immigrant-population-profiles.

Pew's estimate.[31] However, their estimates differ more in some states. For instance, MPI estimates that there are about 50% more undocumented immigrants in California than Pew estimates. They do not provide measures of uncertainty for their estimates so I assume that each state has a standard error that is 10% of the state's point estimate.

- Additional Scenario 2: The Center for Migration Studies (CMS) has developed estimates of the number of undocumented people in each state in 2018.[32] Their methodology is described in two articles that were published in the *Journal of Migration and Security* (Warren 2014, 2019). They estimate there are about 10,543,500 undocumented immigrants in the United States, which is nearly identical to Pew's national estimate.[33] They do not provide measures of uncertainty for their estimates so I assume that each state has a standard error that is 10% of the state's point estimate.
- Additional Scenario 3: Third, I examine a scenario where the national estimates of the number of undocumented immigrants are somewhat too high. To do this, I simply decrease all of my main estimates using Pew's data of the number of undocumented immigrants in each state by 20% to examine the effects on apportionment if the Pew, MPI, and CMS estimates of the total number of undocumented immigrants in the United States are all too high.
- Additional Scenario 4: Fourth, I examine a scenario where the national estimates of the number of undocumented immigrants are much too high. To do this, I decrease all of my main estimates using Pew's data on the number of undocumented immigrants in each state by 40%.

[31] MPI's national estimate is about 8% higher than Pew's estimate.
[32] Their estimates are available at http://data.cmsny.org/state.html.
[33] CMS's national estimate is about 0.5% higher than Pew's estimate.

- Additional Scenario 5: Finally, I examine a scenario where the national estimates of the number of undocumented immigrants are much too low. To do this, I increase all of my main estimates using Pew's data on the number of undocumented immigrants in each state by 50%.

Table 8: Comparison of My Findings with Analyses Based on Alternative Estimates of the Number of Undocumented Immigrants. The table shows the probability that various states would lose seats in each scenario.

State	Main Analysis	Scenario #1 MPI	Scenario #2 CMS	Scenario #3 Pew (80%)	Scenario #4 Pew (60%)	Scenario #5 Pew (150%)
California	72%	100%	93%	49%	36%	92%
Florida	38%	0%	26%	39%	48%	60%
New Jersey	70%	80%	23%	57%	36%	91%
New York	19%	52%	19%	17%	28%	24%
Texas	98%	96%	98%	98%	98%	99.5%

48. Table 8 compares my main findings (the "Main Analysis" column) to analyses based on alternative estimates of the number of undocumented immigrants. It shows each of the states that at least one scenario (including my main analysis) finds has a 33% chance or more of losing a seat if undocumented immigrants are excluded from the apportionment base. For each of these states, it shows the probability that my analysis indicates the state would lose a seat and the probability it would lose a seat under the various alternative scenarios.

49. Overall, all of these analyses yield substantively similar results as my main analysis. In each scenario, Texas has more than 95% chance of losing a congressional seat if un documented immigrants are excluded from the apportionment base. Moreover, in all of the additional scenarios but one, California has about a 50% chance or more of losing a congressional seat. There is also a significant chance that Florida, New Jersey, and New York could lose a seat in most of the scenarios.

B. Robustness to Alternative Modeling Approaches

50. As I discussed above, there are a number of alternative approaches we could use to project the 2020 populations and estimates of undocumented immigrants in each state. In this section, I discuss alternative forecasting methodologies for each of these:

- Additional Scenario 6: For the population forecasts of each state in 2020, I use a forecasting methodology based on the deltas in the two most recent years. In Table 1, I found that this approach was roughly equivalent to the state space model. The state space model is preferable because it is more flexible and provides a measure of uncertainty.
- Additional Scenario 7: For the forecasts of the number of undocumented immigrants in each state in 2020 based on Pew's data, I use a methodology based on a linear time trends over the four most recent years. In Table 4, I found that this approach performed nearly as well as the state space model. The state space model is preferable because it is more flexible and requires fewer assumptions about future time trends.

51. Both of these alternative-modeling strategies produce similar results as my main results (Table 9). In each scenario, Texas is nearly certain to lose a seat. California and New Jersey are likely to lose seats in each scenario. Florida and New York also have significant chances of losing a seat in each scenario.

Table 9: Comparison of My Findings with Alternative Modeling Strategies. The table shows the probability that various states would lose seats in each scenario.

State	Main Analysis	Scenario #6 Alternative Population Forecasts	Scenario #7 Alternative Forecasts of Undoc. Imm.'s
California	72%	84%	75%
Florida	38%	45%	96%
New Jersey	70%	73%	51%
New York	19%	58%	30%
Texas	98%	99.5%	100%

C. Robustness to a Possible Census Undercount

52. The testimony of the former U.S. Census Bureau Director, John H. Thompson, to Congress on July 29, 2020 raises the possibility that the president's memorandum could lead to nonresponse to the Census by hard-to-count populations, including noncitizens and immigrants.[34] This, in turn, could lead the Census to undercount foreign-born people. It is possible that planned reductions in door-to-door canvassing due to COVID-19 could lead to a further undercount of foreign-born people.[35]

53. In this section, I examine whether an undercount of foreign-born people would affect my findings about the effects of excluding undocumented immigrants from the apportionment base. I use my estimates from *New York Immigration Coalition et al* v. *United States Department of Commerce*, No. 18-CV-2921-JMF (S.D. NY) of the number of foreign-born people in each state. I then assess the consequences of a scenario with a 10% undercount of foreign-born people using the same methodology that I use in my main analyses. I am adopting my declaration provided in that matter by reference and include a copy in Appendix B.

Table 10: Comparison of My Findings with Analyses that Assume 10% Undercount of Foreign-born People. The table shows the probability that various states would lose seats in each scenario.

State State	Main Analysis	Scenario #8 Undercount
California	72%	67%
Florida	38%	0%
New Jersey	70%	93%
New York	19%	0%
Texas	98%	76%

[34] See Statement of John H Thompson, Former Director U.S. Census Bureau (August 2013 – June 2017), For the House Committee on Oversight and Reform, U.S. House of Representatives, July 29, 2020 https://tinyurl.com/y67ojjqb.
[35] See https://www.npr.org/2020/07/30/896656747/when-does-census-counting-end-bureau- sends-alarming-mixed-signals and https://www.nytimes.com/2020/08/04/us/2020-census- ending-early.html.

54. Table 10 compares my main findings to the results of this undercount scenario. It shows each state that my analysis indicates has a significant chance of losing a seat if undocumented immigrants are excluded from the apportionment base. Once again, in this scenario Texas is likely to lose a congressional seat if undocumented immigrants are excluded from the apportionment base. California and New Jersey are also likely to lose congressional seats.

D. Comparison with Other Organizations' Analyses

55. There have been a number of studies and reports by various organizations estimating how excluding undocumented immigrants would affect apportionment. These include:

- The Pew Research Center[36]
- The Center for Immigration Studies (CIS)[37]
- The Center for Politics at the University of Virginia (CfP)[38]
- A peer reviewed academic study published in 2019 (Baumle and Poston Jr 2019).

Table 11: Comparison of My Findings with Other Studies. The table shows whether each study finds various states would lose a seat.

State	Main Analysis (1)	Pew (2)	CIS (3)	CfP (4)	Academic Study (5)
Arizona	0.3%				X
California	72%	X	X	X	X
Florida	38%	X			X
New Jersey	70%			X	
New York	19%		X		
Texas	98%	X	X	X	X

56. Table 11 compares my main findings to the results of these studies. It shows each state that at least one study finds would lose a seat if undocumented immigrants are excluded from the apportionment base. For each of these states, it shows the probability that my analysis

[36] See https://www.pewresearch.org/fact-tank/2020/07/24/how-removing-unauthorized- immigrants-from-census-statistics-could-affect-house-reapportionment/
[37] See https://cis.org/sites/default/files/2019-12/camarota-apportionment-12-19_1.pdf.
[38] See http://centerforpolitics.org/crystalball/articles/excluding-undocumented- immigrants-from-the-2020-u-s-house-apportionment/.

indicates the state would lose a seat and an X for each of the other studies that shows it would lose a seat.

57. Overall, each of these four other studies reaches substantively similar conclusions as the ones in this Declaration. They all conclude that California and Texas would lose congressional seats if undocumented immigrants are excluded from the apportionment base. They also find a mix of other states that might lose seats, including Arizona, Florida, New Jersey, and New York.

VII. Conclusion

58. Based on the analyses in this Declaration, I conclude that failing to count undocumented immigrants for apportionment is likely to have effects on the population counts of each state, and the apportionment of representatives across states for the U.S. House. Texas is nearly certain to lose a congressional seat. California and New Jersey are very likely to each lose a congressional seat. Other states, such as Florida and New York could lose seats as well. This would affect political representation in Congress. For instance, it is likely to affect the distribution of federal funds to each state, and the general power that each state holds in Congress.

I reserve the right to amend or supplement my opinions if additional information or materials become available. I declare under penalty of perjury under the laws of the United States that the forgoing is true and correct to the best of my knowledge.

Executed on August 7, 2020 in Bethesda, Maryland.

Chris Warshaw

Christopher Warshaw

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Appendix A

1. Estimates of Overseas Federal Personnel

Table 3: Estimates of Overseas Federal Personnel in each State in 2020.

State	Overseas Personnel
Alabama	7,700
Alaska	7,500
Arizona	11,000
Arkansas	2,900
California	74,900
Colorado	14,200
Connecticut	2,600
Delaware	2,100
Florida	29,500
Georgia	26,800
Hawaii	17,500
Idaho	2,200
Illinois	10,300
Indiana	3,300
Iowa	900
Kansas	8,300
Kentucky	11,200
Louisiana	7,300
Maine	1,100
Maryland	33,600
Massachusetts	2,700
Michigan	2,900
Minnesota	1,600
Mississippi	6,700
Missouri	8,400
Montana	2,000
Nebraska	3,600
Nevada	6,200
New Hampshire	700
New Jersey	5,300
New Mexico	7,000
New York	9,300
North Carolina	44,500
North Dakota	4,000
Ohio	8,600
Oklahoma	10,700
Oregon	1,200
Pennsylvania	6,900
Rhode Island	1,700
South Carolina	16,400
South Dakota	2,000
Tennessee	2,600
Texas	51,500
Utah	4,200
Vermont	300
Virginia	68,800
Washington	23,000
West Virginia	700
Wisconsin	1,600
Wyoming	1,800

2. Estimates of Undocumented Immigrants

Table 5: Estimates of Undocumented Immigrants in each State in 2020. Standard errors, which represent the uncertainty in each estimate, are shown in parentheses.

State	Undocumented Immigrants
Alabama	71,900 (28,800)
Alaska	8,400 (3,500)
Arizona	274,400 (56,400)
Arkansas	65,300 (20,400)
California	2,066,000 (275,700)
Colorado	190,100 (50,200)
Connecticut	148,300 (67,700)
Delaware	29,700 (12,100)
Florida	796,000 (105,300)
Georgia	375,700 (140,000)
Hawaii	43,800 (19,000)
Idaho	38,300 (9,400)
Illinois	409,300 (70,100)
Indiana	103,200 (48,200)
Iowa	51,000 (20,400)
Kansas	81,300 (27,900)
Kentucky	44,700 (20,400)
Louisiana	100,100 (61,500)
Maine	4,000 (1,900)
Maryland	261,600 (76,300)
Massachusetts	231,900 (69,300)
Michigan	103,800 (37,500)
Minnesota	86,800 (34,200)
Mississippi	23,000 (11,600)
Missouri	63,100 (31,300)
Montana	4,400 (1,700)
Nebraska	55,800 (17,900)
Nevada	211,200 (31,600)
New Hampshire	10,400 (4,400)
New Jersey	493,200 (90,000)
New Mexico	59,200 (16,600)
New York	679,800 (102,000)
North Carolina	330,800 (73,400)
North Dakota	5,900 (3,200)
Ohio	94,400 (43,400)
Oklahoma	90,100 (30,200)
Oregon	109,100 (32,200)
Pennsylvania	217,800 (85,500)
Rhode Island	32,900 (12,000)
South Carolina	101,500 (47,500)
South Dakota	5,700 (2,300)
Tennessee	139,200 (56,000)
Texas	1,649,100 (182,200)
Utah	106,100 (19,100)
Vermont	3,500 (1,600)
Virginia	297,600 (104,600)
Washington	274,400 (82,600)
West Virginia	4,300 (2,000)
Wisconsin	72,900 (31,000)
Wyoming	4,800 (1,900)

3. Unrounded Main Results for Congressional Apportionment

Table 12: Unrounded Estimates of Excluding Undocumented Immigrants on Congressional Apportionment

State	Baseline Seats (1)	Seats after Exclusion (2)	Seat Delta (3)	Prob. Seat Loss (4)
Alabama	6.46	7.00	0.54	0%
Alaska	1.00	1.00	0.00	0%
Arizona	10.00	10.00	-0.00	0.3%
Arkansas	4.00	4.00	0.00	0%
California	52.15	51.32	-0.83	72.1%
Colorado	8.00	8.00	-0.00	0.3%
Connecticut	5.00	4.97	-0.03	3.4%
Delaware	1.00	1.00	0.00	0%
Florida	28.86	28.47	-0.38	38.4%
Georgia	14.00	14.02	0.02	0%
Hawaii	2.00	2.00	0.00	0%
Idaho	2.00	2.12	0.12	0%
Illinois	17.00	16.90	-0.10	10.1%
Indiana	9.00	9.00	0.00	0%
Iowa	4.00	4.00	0.00	0%
Kansas	4.00	4.00	0.00	0%
Kentucky	6.00	6.00	0.00	0%
Louisiana	6.00	6.02	0.02	0%
Maine	2.00	2.00	0.00	0%
Maryland	8.00	8.00	0.00	0%
Massachusetts	9.00	9.00	0.00	0%
Michigan	13.00	13.28	0.28	0%
Minnesota	7.07	8.00	0.92	0%
Mississippi	4.00	4.00	0.00	0%
Missouri	8.00	8.00	0.00	0%
Montana	1.92	2.00	0.08	0%
Nebraska	3.00	3.00	0.00	0%
Nevada	4.00	4.00	0.00	0%
New Hampshire	2.00	2.00	0.00	0%
New Jersey	12.00	11.30	-0.70	69.8%
New Mexico	3.00	3.00	0.00	0%
New York	25.54	25.35	-0.19	18.9%
North Carolina	14.00	14.00	0.00	0%
North Dakota	1.00	1.00	0.00	0%
Ohio	15.00	16.00	1.00	0%
Oklahoma	5.00	5.00	0.00	0%
Oregon	6.00	6.00	0.00	0%
Pennsylvania	17.00	17.00	0.00	0%
Rhode Island	1.00	1.17	0.17	0%
South Carolina	7.00	7.00	0.00	0%
South Dakota	1.00	1.00	0.00	0%
Tennessee	9.00	9.00	0.00	0%
Texas	38.99	37.93	-1.06	98.3%
Utah	4.00	4.00	0.00	0%
Vermont	1.00	1.00	0.00	0%
Virginia	11.00	11.16	0.16	0%
Washington	10.00	10.00	0.00	0%
West Virginia	2.00	2.00	0.00	0%
Wisconsin	8.00	8.00	0.00	0%
Wyoming	1.00	1.00	0.00	0%

Appendix B

IN THE UNITED STATES DISTRICT COURT
FOR THE SOUTHERN DISTRICT OF NEW YORK

NEW YORK IMMIGRATION COALITION, *et. al*, Plaintiff, v. UNITED STATES DEPARTMENT OF COMMERCE, *et. al*, Defendant.	Civil Action No. 18-CV-2921-JMF Hon. Jesse M. Furman

DECLARATION OF DR. CHRISTOPHER WARSHAW

I. Qualifications

1. I have been asked by counsel representing the plaintiffs in *New York Immigration Coalition* v. *U.S. Dept of Commerce* and *State of New York* v. *U.S. Dept of Commerce* to analyze relevant data and provide my expert opinions. More specifically, I have been asked: to forecast the populations of every state, county, and city in the United States in 2020; given the assumption that various demographic groups are likely to be undercounted due to the inclusion of a citizenship question on the Census, to estimate the proportion of the population that belongs to those groups; to estimate the proportion of the population in every state, county, and city in the United States that belongs to those demographic groups assumed to be likely to be undercounted in 2020 due to the inclusion of a citizenship question on the Census; to analyze the likely effects of an undercount caused by the citizenship question affecting those same demographic groups on the apportionment of representatives across states for the U.S. House of Representatives; and to examine the likely consequences of an undercount caused by the citizenship question affecting those demographic groups on the

distribution of people in urban and rural counties. My expert report is PX-32 and the errata to that report is PX-323.

2. I have been an Assistant Professor of Political Science at George Washington University since August 2017. Prior to that, I was an Associate Professor at the Massachusetts Institute of Technology from July 2016 - July 2017, and an Assistant Professor at MIT from July 2012 - July 2016.
3. My Ph.D. is in Political Science, from Stanford University, where my graduate training included courses in political science and statistics. I also have a J.D. from Stanford Law School.
4. My academic research focuses on public opinion based on surveys and census data, as well as the study of representation, elections, and polarization in American Politics. I have also taught courses on statistical analysis. My curriculum vitae is PX-323. All publications that I have authored and published appear in my curriculum vitae. My work is published or forthcoming in peer-reviewed journals such as: American Political Science Review, the American Journal of Political Sciences, the Journal of Politics, Political Analysis, Political Science Research and Methods, the British Journal of Political Science, Political Behavior, the Election Law Journal, Nature Energy, Public Choice and edited volumes from Cambridge University Press and Oxford University.
5. I am also on the Editorial Board of the *Journal of Politics*. I have previously provided expert reports in *League of Women Voters of Pennsylvania v. Commonwealth of Pennsylvania* and *League of Women Voters of Michigan* v. *Johnson*. My non-academic writing has been published in the New York Times Upshot.

6. The opinions in this declaration are my own, and do not represent the views of George Washington University.

7. I offer these opinions with a strong degree of professional certainty based on the knowledge I have amassed over my education, training and experience, and through a detailed review of the relevant academic literature.

II. Projecting Future Populations

8. The first stage of my analysis is to develop baseline projections of the population of each state, county, and city in the country in 2020. These projections are critical to determining the likely effects of an undercount in the Census due to the inclusion of a citizenship question. In order to develop these estimates, I use the Census's official estimates of the population of each state, county, and city from 2000-2017. The Census does not provide public estimates of each geographic unit's populations in future years.

A. Data

9. The Census Bureau's Population Estimates Program (PEP) produces estimates of the population for the United States, states, counties, cities, towns, and other geographic areas. These aggregate estimates are based on the demographic components of population change (births, deaths, and migration) at each level of geography.[1]

10. My population projections are based on these official population estimates for each state, county, and city for the period from 2000-2017.

11. For the state populations from 2010-2017, I used the file 'nst-est2017-01.xlsx' which I obtained from https://www.census.gov/data/tables/2017/demo/popest/state-total.html. For the

[1] I do not directly use the more detailed cohort-component method used by the Census for my population projections because this information is unavailable for some geographic levels, particularly for the 2000-2010 period. It is also unclear whether the additional complexities associated with this approach would yield substantial gains in predictive accuracy.

populations from 2000-2009, I used the file 'st-est00int-01.xls' from https://www.census.gov/data/tables/ time-series/demo/popest/intercensal-2000-2010-state.html.

12. For the county populations from 2010-2017, I used the file 'co-est2017-alldata.csv' from https: //www.census.gov/data/tables/2017/demo/popest/counties-total.html. For the populations from 2000-2009, I used the file 'co-est00int-tot.csv' from https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-counties.html.

13. For the county populations from 2010-2017, I used the file 'co-est2017-alldata.csv' from https: //www.census.gov/data/tables/2017/demo/popest/counties-total.html. For the populations from 2000-2009, I used the file 'co-est00int-tot.csv' from https://www.census.gov/data/tables/ time-series/demo/popest/intercensal-2000-2010-counties.html.

14. For the city populations from 2010-2017, I used the data in Factfinder available from https://www.census.gov/data/tables/2017/demo/popest/total-cities-and-towns.html. For the populations from 2000-2009, I used the file 'sub-est00int.csv' from https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-cities-and-towns.html.

B. Statistical Model for Population Projections

15. There are a number of potential options for forecasting the likely population of a geographic unit (e.g., states) in 2020. One possible forecasting option would be to allow the forecasts to increase or decrease over time, where the amount of change over time (called the drift) is set to be the average change in the historical data. *See* Hyndman and Athanasopoulos 2018, at 48-49. Some related methods in this family of forecasting approaches are:

a. Linear trend between 2010-2017: One possibility is to project forward based on the linear trend in the population estimates since the last Census (e.g., Election Data Services 2017). This approach assumes that each geographic unit's population follows the same linear rate of change in the future that it has followed over the past decade. This approach has the benefit of using many years of data, but it could yield biased estimates if the population trends have changed over this period. I estimate linear trends using a simple linear regression model in the software program R.

b. Linear trend between 2014-2017: Another possibility is to project forward based on the linear trend in the population estimates over the past 4 years. This approach assumes that each geographic unit's population follows the same linear trend in the future that it has followed over this shorter time period. This approach has the benefit of being sensitive to more recent trends, but it could be noisier than estimates based on the longer time series. That is, it could be overly sensitive to short-term trends. I estimate linear trends using a simple linear regression model in R.

c. Change between two most recent years (i.e., 2016 to 2017): A third possibility is to focus on the change between each geographic unit's populations in the two most recent years, and assume that future years will follow this recent trend. This approach has the benefit of being based on the most recent changes in populations, but it could also be overly sensitive to short-term idiosyncratic trends. I estimate these short-term trends using the software program R.

16. As Hyndman and Athanasopoulos discuss, "Sometimes one of these simple methods will be the best forecasting method available; but in many cases, these methods will serve as benchmarks rather than the method of choice. That is, any forecasting methods . . . will be compared to these simple methods to ensure that the new method is better than these simple alternatives. If not, the new method is not worth considering." *Id.* at 50.

17. I consider one more complex approach against these benchmarks, a state space model with exponential smoothing: This approach uses an exponential smoothing model that weights levels and trends to an extent determined by the data. *See* Hyndman and Athanasopoulos. This model uses all of the available data, but it gives more weight to the most recent years. I estimate the exponential smoothing model using the ets function in the forecast package in R.[2]

C. Validation of Population Projections

18. The accuracy of forecasting models can only be determined by considering how well a given model performs on new data that were not used when fitting the original model. *Id.* at 62. In order to choose the best model for this analysis, I evaluated each model using two benchmarks that are similar to the challenge of forecasting the 2020 populations. First, I forecasted the Census 2010 population in each state based on 2000-2007 population estimates data. Second, I forecasted the 2017 population estimates in each state based on 2007-2014 population data. For each analysis, I used the following evaluation metrics. *Id.* at 64-65.

[2] For my state-level population projections, I used the default parameters for the ets function in R, which allowed the function to choose the exponential smoothing state space model that best fit the data in each state. The best model was usually an 'MAN' or 'AAN' model. For the population projections for cities and counties, I estimated an 'MAN' state space model using the ets function. The details of the state space model specification, however, do not affect any of my substantive conclusions. All of the state space models yield very similar results.

a. The mean error across states: This helps assess whether a given metric has a systematic bias in one direction or another.

b. The mean absolute error across states: This helps assess the accuracy of the forecasts.

c. The mean absolute proportional error across states: This metric also helps assess the accuracy of the forecasts. It has the advantage of being unit-free (i.e., the interpretation is similar in small and large states).

19. Table 1 shows the results. For the forecast of the 2010 population, the state space model performs the best, with the lowest error, the second lowest mean absolute error, and the lowest absolute proportional errors. The two linear trend models perform the worst on this forecasting exercise. For the forecast of the 2017 population, the state space model and the linear trend model using data from 2010-2017 perform the best. The state space model has slightly lower mean errors, and the two models have similar mean absolute errors and absolute proportional errors.

Table 1: Validation of State Population Projections

Model	2010 Mean Error	2010 Mean Abs. Error	2010 Mean Abs. Prop. Error	2017 Mean Error	2017 Mean Abs Error	2017 Mean Abs. Prop. Error
Linear model (full period)	22,800	62,860	0.013	7,827	32,003	0.007
Linear model (4 years)	27,399	82,106	0.014	33,420	59,396	0.014
Delta in last two years	20,383	50,663	0.010	140,472	142,506	0.020
State space model	5,826	51,033	0.009	-2,599	33,378	0.008

20. Overall, the state space model performs the best across the two validation exercises. It has an average absolute proportional error of only .8% and an average absolute error of only about 40,000 people in each state. As a result, I use the state space model as my main forecasting model to generate population projections. However, the results of all the analyses that follow would be substantively similar using any of these population forecasting approaches.

D. Incorporating Uncertainty

21. All modeled estimates have uncertainty. My analyses use bootstrap simulations to incorporate two sources of uncertainty in all my models:

- The uncertainty in the population forecasts in every geographic unit
- Where available, uncertainty in the undercount estimates for each group

E. Baseline estimates of 2020 populations with no undercount

22. I used the official Census population estimates to project each geographic unit's population in 2020. Table 2 shows the population projections for a selection of cities and counties involved in lawsuits regarding the citizenship question. Table 3 shows the population projections for each state.[3] All of the analysis of apportionment that follows fully incorporates the uncertainties in the projections discussed above. But for simplicity, the tables themselves do not show the uncertainties.

Table 2: Population Projections in Select Counties and Cities

County/City	2010 Population	2017 Population	2020 Population Projection
Phoenix, AZ	1,446,909	1,626,078	1,698,187
Los Angeles County, CA	9,818,605	10,163,507	10,256,275
Monterey County, CA	415,052	437,907	444,016
San Francisco, CA	805,193	884,363	909,143
Miami, FL	399,457	463,347	491,295
Chicago, IL	2,695,620	2,716,450	2,704,974
Price Georges County, MD	863,420	912,756	931,412
New York NY	8,174,959	8,622,698	8,645,147
Columbus, OH	788,877	879,170	925,408
Philadelphia, PA	1,526,006	1,580,863	1,598,072
Pittsburgh, PA	305,391	302,407	297,243
Central Falls, RI	19,393	19,359	19,250
Providence, RI	177,997	180,393	181,532
Cameron County, TX	406,219	423,725	429,603
El Paso County, TX	800,647	840,410	851,600
Hidalgo County, TX	774,770	860,661	892,083
Seattle, WA	608,664	724,745	780,550

[3] The projections shown here do not include the overseas military population, federal employees, and dependents. However, the apportionment projections in Table 5 do include these groups.

Table 3: State population projections

State	2010 Population	2017 Population	2020 Population Projection
Alabama	4,779,736	4,874,747	4,917,351
Alaska	710,231	739,795	739,473
Arizona	6,392,017	7,016,270	7,339,157
Arkansas	2,915,918	3,004,279	3,051,838
California	37,253,956	39,536,653	40,505,540
Colorado	5,029,196	5,607,154	5,823,386
Connecticut	3,574,097	3,588,184	3,589,649
Delaware	897,934	961,939	989,662
District of Columbia	601,723	693,972	722,881
Florida	18,801,310	20,984,400	21,967,862
Georgia	9,687,653	10,429,379	10,776,655
Hawaii	1,360,301	1,427,538	1,429,641
Idaho	1,567,582	1,716,943	1,827,695
Illinois	12,830,632	12,802,023	12,701,647
Indiana	6,483,802	6,666,818	6,761,903
Iowa	3,046,355	3,145,711	3,182,994
Kansas	2,853,118	2,913,123	2,925,781
Kentucky	4,339,367	4,454,189	4,508,391
Louisiana	4,533,372	4,684,333	4,684,247
Maine	1,328,361	1,335,907	1,349,155
Maryland	5,773,552	6,052,177	6,187,649
Massachusetts	6,547,629	6,859,819	6,966,760
Michigan	9,883,640	9,962,311	9,962,308
Minnesota	5,303,925	5,576,606	5,690,791
Mississippi	2,967,297	2,984,100	2,984,630
Missouri	5,988,927	6,113,532	6,180,600
Montana	989,415	1,050,493	1,079,083
Nebraska	1,826,341	1,920,076	1,957,570
Nevada	2,700,551	2,998,039	3,174,453
New Hampshire	1,316,470	1,342,795	1,366,068
New Jersey	8,791,894	9,005,644	9,106,936
New Mexico	2,059,179	2,088,070	2,095,989
New York	19,378,102	19,849,399	19,885,662
North Carolina	9,535,483	10,273,419	10,623,613
North Dakota	672,591	755,393	752,711
Ohio	11,536,504	11,658,609	11,713,096
Oklahoma	3,751,351	3,930,864	3,974,666
Oregon	3,831,074	4,142,776	4,269,590
Pennsylvania	12,702,379	12,805,537	12,838,064
Rhode Island	1,052,567	1,059,639	1,059,639
South Carolina	4,625,364	5,024,369	5,213,894
South Dakota	814,180	869,666	891,229
Tennessee	6,346,105	6,715,984	6,915,723
Texas	25,145,561	28,304,596	29,593,219
Utah	2,763,885	3,101,833	3,274,374
Vermont	625,741	623,657	622,506
Virginia	8,001,024	8,470,020	8,632,998
Washington	6,724,540	7,405,743	7,785,568
West Virginia	1,852,994	1,815,857	1,777,893
Wisconsin	5,686,986	5,795,483	5,858,478
Wyoming	563,626	579,315	565,592

III. Estimating Proportion of People Likely to be Undercounted Due to Citizenship Question

23. I was not asked to and I did not attempt to calculate the specific undercount that the addition of the citizenship question might cause. However, I evaluated a range of potential undercounts of individuals who live in households with at least one non-citizen, Hispanics or foreign-born member to demonstrate the potential effects that the addition of the citizenship question might have. Theory indicates that the addition of a citizenship question could lead to unit non-response, which occurs when a household does not respond to the Census, thereby depressing response rates among non-citizens and immigrant communities. Indeed, the Census acknowledges that it is "a reasonable inference that a question on citizenship would lead to some decline in overall self-response because it would make the 2020 Census modestly more burdensome in the direct sense, and potentially much more burdensome in the indirect sense that it would lead to a larger decline in self-response for noncitizen households." (Abowd 2018, Section B2, p. AR 001281)

24. In my analysis, I use this information to look at three potential undercount scenarios:

    a. First, I used a 5.8% undercount estimate based on the results of the Census Bureau's internal study of the effect of a citizenship question on self-response rates. For these analyses, I assumed that respondents that do not self-respond would not be enumerated.

    b. Second, I was asked by legal counsel to examine a potential 10% undercount for the analysis of state-level apportionment as an outer bound for the potential effects of the citizenship question on population enumerations and apportionment. This higher number reflects the Census's finding that the differences between citizen and noncitizen

response rates and data quality are likely to be "amplified" compared to historical levels (Abowd 2018, Section B4, p. AR 001282). The Chief Scientist at the Census has acknowledged that the 5.8% estimate of the effect of the citizenship question on self-response rates is "a conservative estimate of the differential impact of the citizenship question on the self-response rates of noncitizens compared to citizens" (Abowd, J. Dep., Aug. 15, 2018, p. 202).

c. Third, I was asked by legal counsel to examine a potential 2% undercount as a lower bound for the potential effects of the citizenship question on population enumerations. My report shows the results for cities and counties, and the calculations for a 2% undercount in states are PX-324. I was not asked to and I did not do any analysis of the impact of the Census Bureau's Non-Response Follow-Up ("NRFU") on non-response rates, but note that the 2% scenario could be viewed as taking into account some NRFU success after an initial larger nonresponse rate.

25. The recent Census Bureau studies discussed above focus largely on the effects of a citizenship question on self-response rates in non-citizen households. As a result, the first set of analyses I conducted for each of these undercount scenarios focuses on *people in households with a non-citizen* in them. Beyond the effects on non-citizen households, there are also strong theoretical reasons to believe that *citizen Hispanics* would also be less likely to respond to the Census if a citizenship question is included. Citizen Hispanics in immigrant communities could fear deportation due to their Census responses.[4] Moreover, a large

[4] Title 13, U.S.C. prohibits the use of Census data for enforcement purposes, but respondents may still have this concern (Brown et al. 2018).

fraction of citizen Hispanics are likely to know non-citizens or even people that have been deported. The Census's internal analysis has shown that citizenship-related questions are likely to be more sensitive for Hispanics (Brown et al. 2018, p. 10). Indeed, the Census has found clear evidence there are likely to be differential impacts on self-response rates among Hispanics from the addition of a citizenship question. Hispanics have a greater breakoff rate (i.e., item non-response) on the citizenship question on the American Community Survey (ACS) than other demographic groups.[5] There is also evidence of growing unit nonresponse rates among Hispanics on the ACS (Brown et al. 2018, p. 12). For these reasons, I analyzed the effect of all three undercount scenarios (2%, 5.8% and 10%) on *both people in non-citizen households and citizen Hispanics*.

A. Undercount Estimate Based on Original Survey Experiment

26. An empirical approach to determine the potential undercount caused by a citizenship question is through a randomized control trial (RCT). The Census Bureau suggests that an appropriate RCT could compare self-response rates between households "randomly chosen to have [] a citizenship question (the treated group), and a randomly chosen set of control households [that] receive a [] Census questionnaire without citizenship" (Brown et al. 2018, p. 39)

27. We were unable to conduct a real-world RCT. A similar approach, however, is to conduct an experiment that mimics an RCT on a nationally representative survey of Americans. As part of this case, the State of New York and other plaintiffs funded a nationally representative survey that included an experiment along these lines to examine whether the inclusion of a

[5] *See* Abowd (2018, Section b3) and Brown et al. (2018, 7).

citizenship question would reduce the likelihood that people would complete the Census.[6] This survey was designed by Dr. Matt Barreto and conducted by Pacific Market Research.[7]

1. Design of Survey

28. This survey included a probability sample of 6,309 people, including over-samples of Hispanics, Californians, and people in several cities and counties (San Jose, CA, Cameron County, TX, and Hidalgo County, TX).[8] It was conducted via phone by Pacific Research Group to both landlines and cell phones using live interviews and random digit dialing. The survey asked a number of questions about the Census and assessed reactions to the inclusion of a citizenship question. The survey did not include a question about the citizenship of respondents. But it did include a question about whether respondents were born in the United States or a foreign country.

29. In my analysis, I focus on an experiment embedded in the survey that mimics the RCT approach suggested by Brown et al. (2018). This enables us to estimate the causal effect of the citizenship question on the likelihood that various demographic subgroups will complete the Census.

30. In the experiment on our survey, the control group received a vignette stating that the government had decided not to include a citizenship question on the census, while the treatment group received a vignette stating that the government had decided to include a citizenship question on the census. Then the survey asked whether respondents would 'participate and fill out the 2020 Census form, or not?'

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[6] As part of my work as an expert in this matter, I reviewed Professor Barreto's expert report that describes the survey methodology and his analysis of the results. However, I ran all of the analyses of the survey used in this report myself. I did not directly use any of Professor Barreto's findings for my report.
[7] Data and statistical code to replicate my analysis of this survey is available in my replication materials.
[8] The survey includes sampling weights that incorporate these over-samples and make the results representative at the national-level.

Control Group: Now that you've heard a little bit about the 2020 Census let me ask you one final question about how likely you are to participate. If the government decides in 2020 to NOT include a question about citizenship status, and instead only asks you to report the race, ethnic background, gender of people living in your household, and the government provides assurances that your information will be kept confidential and ONLY used for purposes of counting the total population and nothing more, would you participate and fill out the 2020 Census form, or not?

Treatment Group: Now that you've heard a little bit about the 2020 Census let me ask you one final question about how likely you are to participate. If the government decides in 2020 to include a question about citizenship status, and asks you to report the race, ethnic background, gender and citizenship status of people living in your household, and the government provides assurances that your information will be kept confidential and ONLY used for purposes of counting the total population and nothing more, would you participate and fill out the 2020 Census form, or not?

31. This experimental design is a strong one for assessing the causal effect of the citizenship question on the likelihood that people will complete the Census. However, it does have limitations. First, the experiment on the survey imperfectly captures the actual experience of completing the Census. Second, many respondents are probably already aware of the potential inclusion of the citizenship question on the Census, which could lead to Stable Unit Treatment Value Assumption (SUTVA) violations. These SUTVA violations could attenuate the effects we detect in the experiment by artificially reducing the differences between the treatment and control groups. Overall, I think these limitations mean the survey-based

analysis is conservative in its estimates of the citizenship question on self-response rates on the Census.

2. Results of Survey

32. My primary analyses focus on two immigrant communities that theory indicates are particularly likely to be impacted by the citizenship question. First, I analyze the impact on Latinos.[9] This analysis is helpful because there is little publicly available Census analysis of the potential effects of the citizenship question on this group. Second, I analyze the impact on non-Latino people that are not born in the United States.[10]

33. I ran three sets of analyses that are shown in Table 4. My primary analysis of the effect of the citizenship question on each group is a weighted regression that evaluates the treatment effect of the citizenship question. In other words, it evaluates whether people in the treatment group, that were told the Census would include a citizenship question, are less likely to indicate they would respond to the Census than people in the control group that were told it would not include a citizenship question.

34. As robustness checks, I also ran two additional models. The middle column of Table 4 for each group is a weighted regression model that includes control variables for other factors that might affect respondents' willingness to complete the Census, including their age, race, and state of residence. The third column of Table 4 for each group is an unweighted regression model that includes this same set of control variables for other factors that might affect respondents' willingness to complete the Census. All of my main analyses in the results below are based on linear probability models. However, logistic regression models yield similar results.

[9] Note that I use the terms Hispanic and Latino interchangeably throughout this declaration.

[10] I include in this group both people that explicitly stated they were born in a foreign country and the small number of people that refused to answer the nativity question on the survey.

35. Overall, Table 4 shows that the citizenship question makes both Latinos and Foreign-born non-Latinos less likely to respond to the Census. The weighted regression model in column (1) indicates that Latinos are about 5.9% less likely to complete the Census if it includes a citizenship question. The results are similar in the other two models shown in columns (2) and (3). For foreign-born, non-Latinos, the weighted regression in column (4) indicates that they are about 11.3% less likely to complete the Census if it includes a citizenship question. The results are substantively similar, though more statistically significant, in the other two models shown in columns (5) and (6).

Table 4: Experiment Results on Effects of Citizenship Question on Census Response among Latinos and Foreign-born

	Latinos			Foreign-born (not Latino)		
	(1)	(2)	(3)	(4)	(5)	(6)
Citizenship Question	−0.059**	−0.070**	−0.062***	−0.113	−0.164**	−0.096**
	(0.029)	(0.028)	(0.016)	(0.072)	(0.066)	(0.039)
Survey Weights	X	X		X	X	
Controls		X	X		X	X
Observations	2,362	2,362	2,362	488	488	488
R^2			0.043			0.117
Adjusted R^2			0.021			0.022
Log Likelihood	−2,851.497	−2,763.581		−782.779	−714.807	

Note: *p<0.1; **p<0.05; ***p<0.01

IV. Baseline Estimates of Proportion of Population in Immigrant Communities Vulnerable to Undercount

36. In order to analyze the effects of an undercount of individuals that live in households with at least one non-citizen and Hispanic on total population enumerations, I used the American Community Survey (ACS) to generate baseline estimates of the proportion of the 2020 population in each state, county, and large city in the following groups that are vulnerable to an undercount:

- Non-citizen households (based on whether any member of a household in the ACS self-reports that they are a noncitizen)[11]
- All Hispanics and citizen Hispanics
- Foreign-born, non-Hispanics

37. To forecast the population margins of each group within each state (e.g., percent Hispanic), I used the individual-level data in the American Community Survey (ACS) from 2007-2016 to forecast the 2020 population distributions using the same approach that I used to forecast state populations. Individual-level data in the ACS is not readily available below the state-level (e.g., for counties and cities). As a result, I used population tables published by the Census based on the five-year ACS samples (2012-2016) to estimate the demographic distributions within counties and cities.[12] I did not attempt to estimate how these substate population distributions are likely to change between 2016 and 2020. Thus, my estimates of the percentage of county and city population that are members of immigrant communities are probably low due to the general growth of these populations.

A. State-level Effects of Undercount - Effect of Undercount on State Population Enumerations

38. I analyzed the effects of each undercount scenario on the enumerated population of each state in 2020. The results are shown in Table 5. Column (1) shows the baseline apportionment population projections for each state. Column (2) shows the average change in the enumerated population if 5.8% of people in non-citizen households are not counted due to

[11] It is important to note that the Census has found that the ACS might be drastically undercounting the number of households with noncitizens. The ACS implies that about 10% of people live in households with a noncitizen in them. However, Census Bureau found that many people may be misreporting their citizenship status on the ACS. Based on administrative records, they estimate that 28.6 percent of all households could potentially contain at least one noncitizen. So my estimate of the percentage of people that reside in households with a noncitizen based on the ACS is likely conservative.

[12] For the selection of cities and counties in Tables 2, 7, and 8, I converted the number of *non-citizens* to the number of *people in households with a non-citizen* using the ratio of these groups in the individual-level 5-year ACS sample (2012-16) for people in the PUMAs that overlapped each city and county. This analysis is necessarily approximate since PUMAs in the ACS micro-data contain multiple cities and counties.

the citizenship question. Column (3) shows the average change in the enumerated population if 5.8% of non-citizen households and Hispanics are not counted due to the citizenship question. Column (4) shows the average change in the enumerated population if 10% of people in non-citizen households are not counted due to the citizenship question. Column (5) shows the average change in the enumerated population if 10% of non-citizen households and Hispanics are not counted due to the citizenship question. Column (6) shows the average change in the enumerated population in each state based on the results of the survey experiment. Specifically, this scenario assumes that 5.9% of Hispanics and 11.3% of foreign-born, non-Latinos are not counted in the enumerated population.

39. For the analysis of apportionment, I also incorporated estimates of the overseas military population and federal employees, and their dependents living with them. Specifically, I used the 2010 population figures for the overseas military population and federal employees, and their dependents living with them, for each state, and divided this number by half to approximately reflect the reduction in the nation's military deployments over the past decade. *See* https://www.census.gov/data/tables/2010/dec/2010-apportionment-data.html, for 2010 population figures. *See also* Pew Foundation study, http://www.pewresearch.org/fact-tank/2017/08/22/ u-s-active-duty-military-presence-overseas-is-at-its-smallest-in-decades/, for more information on the reduction in the number of overseas military personnel over the past decade.

Table 5: Effect of Undercount on State Population Enumerations in 2020

State	Baseline Apportionment Pop. Projection	5.8% Undercount Noncitizens	5.8% Undercount Noncitizens+ Hispanic	10% Undercount Noncitizens	10% Undercount Noncitizens + Hispanic	Survey Experiment Foreign-born + Hispanics
	(1)	(2)	(3)	(4)	(5)	(6)
Alabama	4,928,974	-0.3%	-0.4%	-0.5%	-0.7%	-0.6%
Alaska	745,119	-0.5%	-0.8%	-0.8%	-1.4%	-1.4%
Arizona	7,349,498	-0.9%	-2.1%	-1.5%	-3.6%	-2.6%
Arkansas	3,056,993	-0.4%	-0.6%	-0.7%	-1%	-0.8%
California	40,549,557	-1.7%	-2.9%	-2.9%	-5%	-4.1%
Colorado	5,831,253	-0.7%	-1.5%	-1.2%	-2.7%	-2%
Connecticut	3,593,415	-0.8%	-1.5%	-1.3%	-2.6%	-2.4%
Delaware	991,133	-0.6%	-1%	-1%	-1.7%	-1.5%
Florida	22,017,594	-1%	-2%	-1.7%	-3.4%	-2.7%
Georgia	10,796,611	-0.7%	-0.9%	-1.2%	-1.6%	-1.5%
Hawaii	1,432,921	-1%	-1.6%	-1.7%	-2.8%	-3%
Idaho	1,830,654	-0.4%	-0.9%	-0.8%	-1.6%	-1.2%
Illinois	12,718,521	-0.8%	-1.4%	-1.4%	-2.4%	-2.1%
Indiana	6,770,793	-0.4%	-0.6%	-0.7%	-1.1%	-0.9%
Iowa	3,186,710	-0.4%	-0.6%	-0.7%	-1%	-0.9%
Kansas	2,931,128	-0.6%	-1%	-1%	-1.7%	-1.3%
Kentucky	4,514,011	-0.3%	-0.4%	-0.5%	-0.7%	-0.6%
Louisiana	4,694,542	-0.3%	-0.5%	-0.5%	-0.8%	-0.6%
Maine	1,351,512	-0.2%	-0.3%	-0.3%	-0.5%	-0.6%
Maryland	6,195,838	-0.9%	-1.2%	-1.6%	-2%	-2.1%
Massachusetts	6,972,768	-0.9%	-1.4%	-1.5%	-2.4%	-2.4%
Michigan	9,976,301	-0.4%	-0.6%	-0.6%	-1%	-1.1%
Minnesota	5,696,268	-0.5%	-0.6%	-0.8%	-1.1%	-1.2%
Mississippi	2,990,101	-0.2%	-0.3%	-0.3%	-0.5%	-0.4%
Missouri	6,191,875	-0.2%	-0.4%	-0.4%	-0.7%	-0.7%
Montana	1,081,584	-0.1%	-0.3%	-0.2%	-0.6%	-0.5%
Nebraska	1,960,312	-0.5%	-0.9%	-0.9%	-1.5%	-1.2%
Nevada	3,178,894	-1.3%	-2.1%	-2.2%	-3.6%	-3%
New Hampshire	1,368,556	-0.3%	-0.5%	-0.5%	-0.8%	-0.9%
New Jersey	9,114,740	-1.2%	-1.9%	-2%	-3.3%	-3%
New Mexico	2,100,036	-0.8%	-3.1%	-1.3%	-5.3%	-3.3%
New York	19,907,138	-1.2%	-1.9%	-2.1%	-3.2%	-3.1%
North Carolina	10,638,762	-0.6%	-0.8%	-1%	-1.4%	-1.2%
North Dakota	754,368	-0.2%	-0.4%	-0.4%	-0.7%	-0.7%
Ohio	11,729,092	-0.2%	-0.4%	-0.4%	-0.7%	-0.7%
Oklahoma	3,981,432	-0.5%	-0.8%	-0.8%	-1.4%	-1.1%
Oregon	4,278,356	-0.7%	-1.1%	-1.1%	-1.9%	-1.6%
Pennsylvania	12,854,327	-0.4%	-0.7%	-0.6%	-1.3%	-1.2%
Rhode Island	1,060,979	-0.7%	-1.3%	-1.2%	-2.3%	-2%
South Carolina	5,224,199	-0.3%	-0.5%	-0.6%	-0.9%	-0.8%
South Dakota	894,019	-0.3%	-0.4%	-0.5%	-0.8%	-0.7%
Tennessee	6,930,386	-0.4%	-0.5%	-0.6%	-0.9%	-0.8%
Texas	29,654,648	-1.3%	-2.7%	-2.2%	-4.6%	-3.2%
Utah	3,277,814	-0.6%	-1.1%	-1.1%	-1.9%	-1.4%
Vermont	624,804	-0.2%	-0.3%	-0.3%	-0.5%	-0.7%
Virginia	8,651,354	-0.7%	-1%	-1.2%	-1.7%	-1.8%
Washington	7,799,983	-0.9%	-1.3%	-1.5%	-2.2%	-2.2%
West Virginia	1,781,304	-0.1%	-0.2%	-0.2%	-0.3%	-0.3%
Wisconsin	5,864,100	-0.3%	-0.6%	-0.6%	-1.1%	-0.9%
Wyoming	567,929	-0.3%	-0.8%	-0.5%	-1.3%	-1%

40. Overall, Table 5 indicates that each state would be affected by an undercount on the Census. The largest impacts would be in states with large numbers of Hispanics, non-Citizens, and foreign-born residents. For example, California would be undercounted by 1.7-5.0% in these scenarios; Florida would be undercounted by 1-3.4%; New Jersey would be undercounted by

1.2-3.3%, New York would be undercounted by 1.2-3.2%; and Texas would be undercounted by 1.3-4.6%.

41. Figure 1 shows a map of the results from the survey experiment (column 6 in Table 5). This map graphically shows that heavily Latino states on the southern border have the largest impacts from an undercount. States in the northeast, such as New York, New Jersey, and Massachusetts, with significant foreign-born populations also have significant impacts.

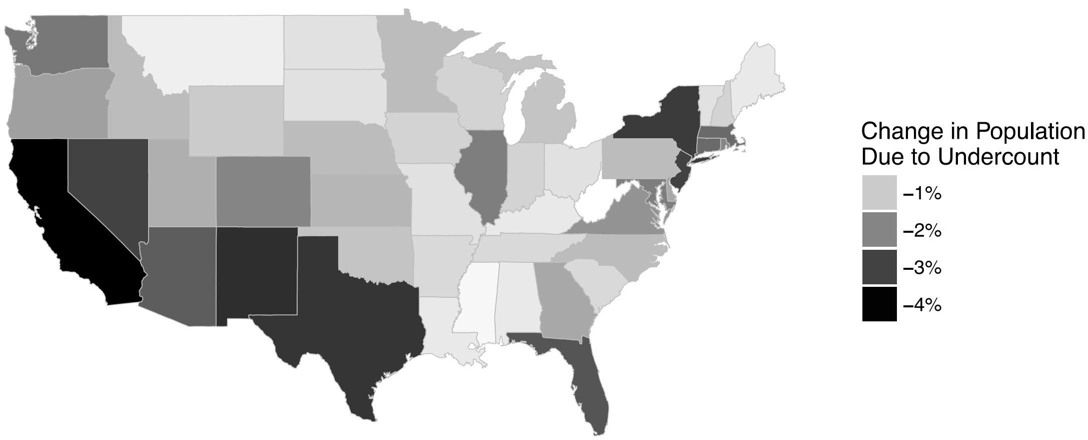

Figure 1: Effects on State Populations

42. I used the population projections and estimated effects of the various undercount scenarios on the enumerated population of each state to examine the likely effect of the citizenship question on the apportionment of seats in the House of Representatives. Article 1, Section 2, of the United States Constitution states: "Representatives and direct Taxes shall be apportioned among the several States which may be included within this Union, according to their respective Numbers."

43. Since the first census in 1790, five methods of apportionment have been used. The government currently uses a method called the Method of Equal Proportions, which was

adopted by Congress in 1941 following the census of 1940. This method first assigns each state one seat. Then, additional seats in the House of Representatives are signed to a "priority" value. The priority value for each seat is determined by multiplying the population of a state by a "multiplier." The multiplier is $1/\sqrt{n(n-1)}$. So the formula for calculating the multiplier for the second seat is $1/\sqrt{2(2-1)}$ or 0.70710678, the formula for calculating the multiplier for the third seat is $1/\sqrt{3(3-1)}$ or 0.40824829, and so on. The Census provides an official table of these multipliers, which I used for my calculations.[13]

44. The next step is to multiply the multipliers by the population total for each of the 50 states (the District of Columbia is not included in these calculations). The resulting numbers are the priority values. Multipliers and priority values must be calculated for the largest number of seats that could be assigned to a state. In my analysis, I calculated the priority values for each state for seats 2 through 60. The next step is to rank and number the resulting priority values starting with seat 51 until all 435 seats have been assigned. The final step is to tally the number of seats for each state to arrive at the total number of seats in the House of Representatives apportioned to each state.

45. I conducted these steps for 500 simulations of the population projections and undercount scenarios in each state. Table 6 shows the results. Column (1) shows the baseline projections for the number of seats that each state is likely to receive in 2020 if there is a full population enumeration. Column (2) shows the average change in the number of congressional seats if 5.8% of people in non-citizen households are not counted due to the citizenship question. Column (3) shows the average change in seats if 5.8% of non-citizen households and Hispanics are not counted due to the citizenship question. Column (4) shows the average

[13] *See* https://www.census.gov/population/apportionment/about/computing.html.

change in seats if 10% of people in non-citizen households are not counted due to the citizenship question. Column (5) shows the average change if 10% of non-citizen households and Hispanics are not counted due to the citizenship question. Column (6) shows the average change in seats in each state based on the results of the survey experiment. Specifically, this scenario assumes that 5.9% of Hispanics and 11.3% of foreign-born, non-Latinos are not counted in the enumerated populations. Also, each column includes 95% confidence intervals for the seat projections in parentheses. This means that there is a 95% chance that the true number of seats gained or lost in each scenario will be in this range.

46. First, we can examine Columns (2) and (3) of Table 6, which show the effects of a 5.8% undercount of people in non-citizens households and Hispanics. In these scenarios, California is extremely likely to lose a seat. Additionally, if there is an undercount of 5.8% of both people in non-citizen households and Hispanics, there is more than a 51% chance that Texas will lose a seat. There is also a risk that Arizona, Florida, Illinois, and New York could lose seats in some simulations.

47. Columns (4) and (5) of Table 6 show the effects of a 10% undercount of non-citizen households and Hispanics. If only people in non-citizen households are undercounted, California and Texas would be more likely than not to lose a seat. Arizona, Florida, Illinois, and New York would also be at risk of losing seats. If both non-citizens and Hispanics are undercounted, Arizona, California, Florida, and Texas would be likely to lose seats. Illinois and New York would also be at risk of losing a seat.

Table 6: Effect of Undercount on Congressional Apportionment

State	Baseline Seats	5.8% Undercount Noncitizens	5.8% Undercount Noncitizens+ Hispanic	10% Undercount Noncitizens	10% Undercount Noncitizens + Hispanic	Survey Experiment Foreign-born + Hispanics
Alabama	6	0 (0,1)	1 (0,1)	1 (0,1)	1 (0,1)	1 (0,1)
Alaska	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Arizona	10	0 (-1,0)	0 (-1,0)	0 (-1,0)	-1 (-1,0)	0 (-1,0)
Arkansas	4	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
California	53	-1 (-1,0)	-1 (-1,0)	-1 (-1,0)	-1 (-2,-1)	-1 (-2,0)
Colorado	8	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Connecticut	5	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Delaware	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Florida	29	0 (-1,0)	0 (-1,0)	0 (-1,0)	-1 (-1,0)	-1 (-1,0)
Georgia	14	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,1)	0 (0,0)
Hawaii	2	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Idaho	2	0 (0,0)	0 (0,0)	0 (0,1)	0 (0,1)	0 (0,1)
Illinois	17	0 (-1,0)	0 (0,1)	0 (-1,1)	0 (-1,0)	0 (-1,0)
Indiana	9	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Iowa	4	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Kansas	4	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Kentucky	6	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Louisiana	6	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,1)	0 (0,0)
Maine	2	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Maryland	8	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Massachusetts	9	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Michigan	13	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Minnesota	7	0 (0,1)	0 (0,1)	0 (0,1)	1 (0,1)	1 (0,1)
Mississippi	4	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Missouri	8	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Montana	1	1 (0,1)	1 (0,1)	1 (0,1)	1 (0,1)	1 (0,1)
Nebraska	3	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Nevada	4	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
New Hampshire	2	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
New Jersey	12	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
New Mexico	3	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
New York	26	0 (-1,0)	0 (0,0)	0 (-1,0)	0 (-1,0)	0 (-1,0)
North Carolina	14	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
North Dakota	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Ohio	15	0 (0,0)	0 (0,1)	0 (0,1)	1 (0,1)	0 (0,1)
Oklahoma	5	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Oregon	6	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Pennsylvania	17	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Rhode Island	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
South Carolina	7	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
South Dakota	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Tennessee	9	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Texas	39	0 (-1,0)	-1 (-1,0)	-1 (-1,0)	-1 (-1,0)	-1 (-1,0)
Utah	4	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Vermont	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Virginia	11	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Washington	10	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
West Virginia	2	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Wisconsin	8	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)
Wyoming	1	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)

48. Column (6) shows the effects of the undercount of Hispanics and foreign-born residents found in the survey experiment. In this scenario, California, Florida, and Texas would most likely all lose seats. Arizona, Illinois, and New York could lose a seat as well.

49. The states that lose seats in Congress would likely see decreases in their share of outlays of federal funding due to their reduction in voting power in Congress. *See* Elis, Malhotra, and Meredith 2009 (PX-325). The Elis article attached here is just an example. It is a well-established finding in political science and political economy that the loss of political power as a result of the loss of representation leads to the loss of funding. This finding is based on a body of research showing that counties in areas of states that were underrepresented in state legislatures or Congress due to malapportionment received substantially lower shares of distributive spending. In the wake of the *Baker v. Carr* family of Supreme Court cases that required one-person, one-vote, counties that were underrepresented due to malapportionment saw both their representation in legislatures and their share of spending increase substantially when the equal populace district requirement was implemented. *See* Ansolabehere, Gerber, and Snyder 2002 (PX-326). Additionally, it is also based on another body of research comparing states that barely gain or lose Representatives in Congress. *See* PX-325. The census thresholds sometimes are quite close where a state could gain or lose seats. So this research compares those states that are just above and below the population thresholds to gain or lose a seat, and it has found that the states that just barely gain a seat receive more money than the states that barely lose a seat.

B. City and County Effects of Undercount

50. I also examined the effects of the various undercount scenarios for cities and counties. Irrespective of state-level impacts on apportionment, the enumeration of subnational areas is crucially important for a number of purposes. It affects the distribution of federal and state funds that are tied to population formulas. In addition, it affects the allocation of legislative seats within states since legislative districts are required to be equipopulous.

51. This allocation of voting power within states, in turn, affects distributive spending programs influenced by the legislature. *See* PX-326. Areas with greater population enumerations, and thus more voting power, are likely to receive more funding. This article is just another example of this well-established finding in political science. There is a large body of political science research concluding that vote dilution due to malapportionment leads to a reduction in voting power and less distributive spending.

52. It is reasonable to assume that undercounts like those addressed in my report will more likely than not impact intrastate redistricting because there is no reason to think that a state legislature would correct an undercount on the Census. I think it's a reasonable assumption that state governments would not consciously try to remedy an undercount.

53. Table 7 shows the impact on the counties and cities that are involved in the lawsuits regarding the citizenship question. The left column shows the baseline 2020 population projection. It also shows the absolute change in population and percentage change in the geographic unit's population due to three undercount scenarios. First, I examine a 2% undercount scenario. Second, I examine a 5.8% undercount scenario. For each of these scenarios, I examine undercounts among people in non-citizen households and among non-citizens households + Hispanics. Finally, I examine a scenario based on the results of the survey experiment.

54. Table 7 shows the effects on a selection of cities and counties involved in the lawsuits regarding the citizenship question. All of these local governments would most likely face smaller population enumerations due to an undercount from the addition of a citizenship question. Some of the largest effects would be in Miami, FL, New York, NY, Central Falls,

RI, and Providence RI. In the survey experiment scenario (right-hand column), each of these cities could see a reduction of around 4% or more in their enumerated populations.

Table 7: Effect on Population Counts in Select Counties and Cities

		2% Undercount				5.8% Undercount				Survey Experiment	
		Noncitizens		Noncitizens+ Hispanics		Noncitizens		Noncitizens+ Hispanics		Foreign-born+ Hispanics	
County	2020 Population	Abs. Change	% Change	Abs. Change	% Change	Abs. Change	% Change	Abs. Change	% Change	Abs. Change	% Change
Phoenix, AZ	1,698,187	9,532	-0.6%	15,939	-0.9%	27,644	-1.6%	46,223	-2.7%	53,388	-3.1%
Los Angeles County, CA	10,256,275	74,027	-0.7%	118,962	-1.2%	214,679	-2.1%	344,988	-3.4%	469,163	-4.6%
Monterey County, CA	444,016	3,841	-0.9%	5,525	-1.2%	11,139	-2.5%	16,022	-3.6%	18,215	-4.1%
San Francisco, CA	909,143	4,640	-0.5%	6,141	-0.7%	13,457	-1.5%	17,808	-2%	37,509	-4.1%
San Jose, CA	1,045,953	6,843	-0.7%	10,743	-1%	19,845	-1.9%	31,153	-3%	52,766	-5%
Washington, DC	722,881	1,997	-0.3%	2,690	-0.4%	5,792	-0.8%	7,800	-1.1%	11,859	-1.6%
Miami, FL	491,295	4,868	-1%	7,734	-1.6%	14,118	-2.9%	22,428	-4.6%	24,713	-5%
Chicago, IL	2,704,974	12,334	-0.5%	20,052	-0.7%	35,769	-1.3%	58,152	-2.1%	76,859	-2.8%
Prince Georges County, MD	931,412	4,388	-0.5%	5,054	-0.5%	12,724	-1.4%	14,658	-1.6%	21,592	-2.3%
New York, NY	8,645,147	55,293	-0.6%	83,728	-1%	160,350	-1.9%	242,811	-2.8%	396,647	-4.6%
Columbus, OH	925,408	2,375	-0.3%	2,768	-0.3%	6,886	-0.7%	8,027	-0.9%	12,889	-1.4%
Philadelphia, PA	1,598,072	3,944	-0.2%	7,305	-0.5%	11,438	-0.7%	21,185	-1.3%	32,116	-2%
Pittsburgh, PA	297,243	480	-0.2%	614	-0.2%	1,392	-0.5%	1,780	-0.6%	3,124	-1.1%
Central Falls, RI	19,250	190	-1%	313	-1.6%	550	-2.9%	908	-4.7%	920	-4.8%
Providence, RI	181,532	1,249	-0.7%	1,934	-1.1%	3,622	-2%	5,608	-3.1%	6,833	-3.8%
Cameron County, TX	429,603	3,535	-0.8%	7,759	-1.8%	10,253	-2.4%	22,501	-5.2%	23,272	-5.4%
El Paso County, TX	851,600	5,844	-0.7%	14,227	-1.7%	16,947	-2%	41,259	-4.8%	43,069	-5.1%
Hidalgo County, TX	892,083	8,455	-0.9%	16,540	-1.9%	24,520	-2.7%	47,965	-5.4%	49,626	-5.6%
Seattle, WA	780,550	2,483	-0.3%	2,987	-0.4%	7,200	-0.9%	8,661	-1.1%	17,083	-2.2%

55. The three Texas counties would also face particularly negative impacts. Each of these heavily Latino counties could have a reduction in their enumerated populations of over 5%.

56. Figure 2 shows the reduction in the enumerated population for every county in the country based on the survey experiment (last column of Table 7). It shows that the largest effects are in counties on the southern border, the California coast, and in the region around New York City. The counties and cities that are plaintiffs in this suit are labeled on the graph. All of these geographic units are in the most heavily impacted areas of the country.

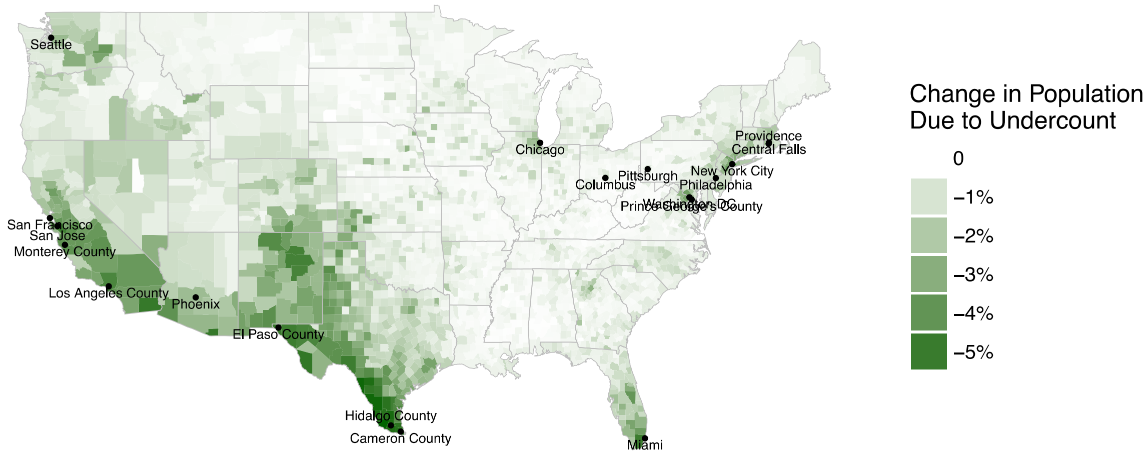

Figure 2: Effects on County Populations

57. Table 8 shows the change in each area's share of its state population due to the undercount. This statistic is important for estimating the potential effects of the undercount on state-level formula grants, as well as on the relative voting power of each geographic area in congressional and state legislative elections. Geographic areas that see a reduction in their share of the state population are likely to get less representation in Congress and their state legislature. This reduction in voting power is likely to lead to less distributive spending. *See* PX-326. As stated before, this article is just an example. There is a large body of political science research that finds localities have their vote diluted because they are malapportioned. This implies that if the enumerated populations used for redistricting are smaller than their actual populations, then this reduction in voting power is very likely to lead to less distributive spending.

Table 8: Effect on Relative Representation in Select Counties and Cities

	2% Undercount		5.8% Undercount		Survey Experiment
	Noncitizens	Noncitizens+ Hispanics	Noncitizens	Noncitizens+ Hispanics	Foreign-born+ Hispanics
Phoenix, AZ	-0.4%	-0.4%	-0.9%	-0.8%	-0.7%
Los Angeles County, CA	-0.3%	-0.3%	-0.5%	-0.6%	-0.6%
Monterey County, CA	-0.4%	-0.4%	-1%	-0.9%	-0.1%
San Francisco, CA	0%	0.2%	0.1%	0.8%	-0.2%
San Jose, CA	-0.2%	-0.1%	-0.3%	-0.2%	-1.1%
Miami, FL	-0.9%	-1.1%	-2.1%	-2.9%	-2.6%
Chicago, IL	-0.3%	-0.4%	-0.6%	-0.9%	-0.9%
Prince Georges County, MD	-0.3%	-0.3%	-0.6%	-0.5%	-0.4%
New York, NY	-0.3%	-0.4%	-0.8%	-1.1%	-1.6%
Columbus, OH	-0.3%	-0.3%	-0.6%	-0.6%	-0.8%
Philadelphia, PA	-0.2%	-0.3%	-0.5%	-0.7%	-1%
Pittsburgh, PA	-0.2%	-0.1%	-0.2%	0%	0%
Central Falls, RI	-0.9%	-1.3%	-2.3%	-3.5%	-2.9%
Providence, RI	-0.6%	-0.7%	-1.4%	-1.9%	-1.9%
Cameron County, TX	-0.6%	-1.1%	-1.3%	-2.8%	-2.5%
El Paso County, TX	-0.5%	-1%	-0.9%	-2.4%	-2.1%
Hidalgo County, TX	-0.7%	-1.2%	-1.7%	-3%	-2.7%
Seattle, WA	-0.2%	-0.1%	-0.2%	0%	-0.2%

58. Table 8 shows the relative change in each area's population using three undercount scenarios. First, I examine a 2% undercount scenario. Second, I examine a 5.8% undercount assumption. For each of these scenarios, I examine undercounts among people in non-citizen households and among non-citizens households + Hispanics. Finally, I examine a scenario based on the results of the survey I discussed in depth above.

59. Under nearly every scenario, each of the cities and counties would face declines in their share of their respective state populations due to an undercount from the citizenship question. Once again, some of the largest effects would be in Miami, FL, New York, NY, Central Falls, RI, Providence RI, and the three Texas counties. Each of these areas would have a reduction in their 'relative populations' (i.e., share of the state population) of several percentage points based on the survey experiment.

V. Aggregate Effects on Share of Population in Different Types of Counties

60. I examined the macro effects of an undercount due to the addition of a citizenship question on the distribution of the enumerated population across urban and rural areas. For simplicity, I use the survey estimates on foreign-born people and Hispanics. But the results are broadly similar for other undercount scenarios.[14] The best available definition of urban and rural areas is based on a classification system developed by the National Center for Health Statistics (NCHS).[15] This classification system is often used to study the associations between the urbanization level of residence and health and to monitor the health of urban and rural residents. NCHS has developed a six-level urban-rural classification scheme for U.S. counties and county-equivalent entities. The most urban category consists of "central" counties of large metropolitan areas and the most rural category consists of nonmetropolitan "noncore" counties. Figure 3 shows a map of the NCHS classification scheme.

[14] For confidentiality reasons, it is not possible to match the ACS micro-data to smaller cities and counties. So, for this analysis, I calculated the ratio of people in non-citizen households to individual non-citizens for each state in the 2016 ACS. I then multiplied these ratios by the estimates of the number of non-citizens in each city and county to estimate the number of people in households with a non-citizen.
[15] *See* https://www.cdc.gov/nchs/data_access/urban_rural.htm.

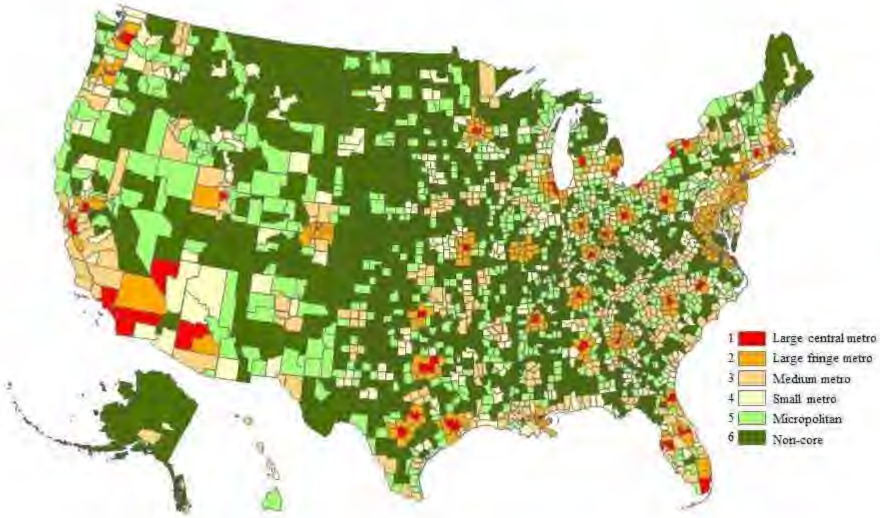

Figure 3: 2013 Urban-Rural Classification Scheme for Counties

61. Figure 3 shows that an undercount due to a citizenship question would have the most substantial impact in large metropolitan counties with major cities. Based on the survey experiment, these counties would have a reduction in their enumerated population of 2.9%.[16] This group of counties would also have a reduction in their share of the national population of 1.1%. This reduction in urban areas' relative population would likely lead to dilution in their voting power and a reduction in their representation in Congress and state legislatures. At the other end of the continuum, noncore rural counties would only have a reduction in their enumerated population of .5%. Moreover, they would actually see a sizable 1.4% increase in their share of the national population. This would lead to an increase in their representation in the legislature. Thus, the undercount caused by a citizenship question on the

[16] The patterns are broadly similar in the other scenarios.

Census would lead to a redistribution of political power in America. It would reduce the representation of urban counties, and increase the voting power of rural counties.

Table 9: Effect on Distribution of Enumerated Population Across Urban and Rural Counties

County	2020 Population Projection	Percentage Change Due to Undercount	Percentage Change in Relative Population
Large central metro	103,025,259	-2.9%	-1.1%
Large fringe metro	83,761,694	-1.8%	.1%
Median metro	69,737,033	-1.5%	.3%
Small metro	30,116,705	-1%	.9%
Micropolitan	27,375,961.605	-.8%	1.1%
Noncore	18,760,860	-.5%	1.4%

VI. Conclusion

62. I have reached the following conclusions:

a. The undercount caused by the inclusion of a citizenship question on the Census is likely to have effects on the population counts of each state, and the apportionment of representatives across states for the U.S House. There is a very high probability that California will lose a congressional seat, and it is more likely than not that Texas will lose a congressional seat. There is also a substantial risk that Arizona, Florida, Illinois, and New York could lose a seat.

b. The citizenship question is also likely to have effects on the population counts of large counties and cities within each state. This will affect the distribution of voting power within states, and lead to the dilution of the voting power of New York, NY, Miami, FL, Providence, RI, and other large cities with substantial immigrant populations.

c. Overall, the citizenship question will lead to a large-scale shift in the distribution of political power in the United States. It would dilute the voting power of urban counties, and increase the voting power of rural counties.

I declare under penalty of perjury that the foregoing is true and correct.

Executed on: October 26, 2018

Washington, DC

Chris Warshaw

Christopher Warshaw

Appendix

Table A1: Effect of 2% Undercount on State Population Enumerations in 2020

State	Baseline Apportionment Pop. Projection	Noncitizens	Noncitizens+ Hispanic
Alabama	4,928,974	-0.1%	-0.1%
Alaska	745,119	-0.2%	-0.3%
Arizona	7,349,498	-0.3%	-0.7%
Arkansas	3,056,993	-0.1%	-0.2%
California	40,549,557	-0.6%	-1%
Colorado	5,831,253	-0.2%	-0.5%
Connecticut	3,593,415	-0.3%	-0.5%
Delaware	991,133	-0.2%	-0.3%
Florida	22,017,594	-0.3%	-0.7%
Georgia	10,796,611	-0.2%	-0.3%
Hawaii	1,432,921	-0.3%	-0.6%
Idaho	1,830,654	-0.2%	-0.3%
Illinois	12,718,521	-0.3%	-0.5%
Indiana	6,770,793	-0.1%	-0.2%
Iowa	3,186,710	-0.1%	-0.2%
Kansas	2,931,128	-0.2%	-0.3%
Kentucky	4,514,011	-0.1%	-0.1%
Louisiana	4,694,542	-0.1%	-0.2%
Maine	1,351,512	-0.1%	-0.1%
Maryland	6,195,838	-0.3%	-0.4%
Massachusetts	6,972,768	-0.3%	-0.5%
Michigan	9,976,301	-0.1%	-0.2%
Minnesota	5,696,268	-0.2%	-0.2%
Mississippi	2,990,101	-0.1%	-0.1%
Missouri	6,191,875	-0.1%	-0.1%
Montana	1,081,584	0%	-0.1%
Nebraska	1,960,312	-0.2%	-0.3%
Nevada	3,178,894	-0.4%	-0.7%
New Hampshire	1,368,556	-0.1%	-0.2%
New Jersey	9,114,740	-0.4%	-0.7%
New Mexico	2,100,036	-0.3%	-1.1%
New York	19,907,138	-0.4%	-0.6%
North Carolina	10,638,762	-0.2%	-0.3%
North Dakota	754,368	-0.1%	-0.1%
Ohio	11,729,092	-0.1%	-0.1%
Oklahoma	3,981,432	-0.2%	-0.3%
Oregon	4,278,356	-0.2%	-0.4%
Pennsylvania	12,854,327	-0.1%	-0.3%
Rhode Island	1,060,979	-0.2%	-0.5%
South Carolina	5,224,199	-0.1%	-0.2%
South Dakota	894,019	-0.1%	-0.2%
Tennessee	6,930,386	-0.1%	-0.2%
Texas	29,654,648	-0.4%	-0.9%
Utah	3,277,814	-0.2%	-0.4%
Vermont	624,804	-0.1%	-0.1%
Virginia	8,651,354	-0.2%	-0.3%
Washington	7,799,983	-0.3%	-0.4%
West Virginia	1,781,304	0%	-0.1%
Wisconsin	5,864,100	-0.1%	-0.2%
Wyoming	567,929	-0.1%	-0.3%

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Academic Employment

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Massachusetts Institute of Technology, Cambridge, MA

Associate Professor of Political Science (without tenure), 2016 - 2017

Assistant Professor of Political Science, 2012 - 2016

Education

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Fields: American Politics, Comparative Politics, and Political Methodology (Statistics)

Stanford Law School, Juris Doctorate, 2011

Williams College, B.A., *magna cum laude*, 2002

Research Interests

American Politics, Representation, Elections, Public Opinion, State & Local Politics, Environmental Politics and Policy, Statistical Methodology

Research

Publications

Peer Reviewed Articles

22. "The Impact of Partisan Gerrymandering on Political Parties." Forthcoming. *Legislative Studies Quarterly*. (with Nicholas Stephanopoulos)

21. "Using Screeners to Measure Respondent Attention on Self-Administered Surveys: Which Items and How Many?" Forthcoming. *Political Science Research and Methods*. (with Adam Berinsky, Michele Margolis, and Mike Sances)

20. "Accountability for the Local Economy at All Levels of Government in United States Elections." Forthcoming. 2020. *American Political Science Review* .114(3): 660-676. (with Justin de Benedictis-Kessner)
19. "Politics in Forgotten Governments: The Partisan Composition of County Legislatures and County Fiscal Policies." 2020. *Journal of Politics*. 82(2): 460-475. (with Justin de Benedictis-Kessner)
18. "On the Representativeness of Primary Electorates." 2020. *British Journal of Political Science*. 50(2): 677-685. (with John Sides, Chris Tausanovitch, and Lynn Vavreck)
17. "Geography, Uncertainty, and Polarization." 2019. *Political Science Research and Methods*. 7(4): 775-794. (with Nolan McCarty, Jonathan Rodden, Boris Shor, and Chris Tausanovitch)
16. "Policy Ideology in European Mass Publics, 1981–2016." 2019. *American Political Science Review*. 113(3): 674-693. (with Devin Caughey and Tom O'Grady).
15. "Does Global Warming Increase Public Concern About Climate Change?" 2019. *Journal of Politics*. 81(2): 686-691. (with Parrish Bergquist)
14. "Local Elections and Representation in the United States." 2019. *Annual Review of Political Science*. 22(1): 461-479.
13. "The Ideological Nationalization of Party Constituencies in the American States". 2018. *Public Choice*. Keith Poole Symposium. 176(1-2): 133-151. (with James Dunham and Devin Caughey)
12. "Policy Preferences and Policy Change: Dynamic Responsiveness in the American States, 1936-2014." 2018. *American Political Science Review*. 112(2): 249-266. (with Devin Caughey)
11. "Does the Ideological Proximity Between Candidates and Voters Affect Voting in U.S. House Elections?" 2018. *Political Behavior*. 40(1): 223-245. (with Chris Tausanovitch)
10. "Partisan Gerrymandering and the Political Process: Effects on Roll-Call Voting and State Policies." *Election Law Journal.* December, 2017. 16(4): 453-469. Symposium on Partisan Gerrymandering and the Efficiency Gap. (with Devin Caughey and Chris Tausanovitch)
9. "Incremental Democracy: The Policy Effects of Partisan Control of State Government." 2017. *Journal of Politics*. 79(4): 1342-1358. (with Devin Caughey and Yiqing Xu)
8. "Renewable energy policy design and framing influences public support in the United States." 2017. *Nature Energy*. 2(17107). (with Leah Stokes)
7. "Estimating Candidates' Political Orientation in a Polarized Congress." 2017. *Political Analysis*. 25(2): 167-187. (with Chris Tausanovitch)
6. "The Dynamics of State Policy Liberalism, 1936-2014." 2016. *American Journal of Political Science*. 60(4): 899-913. (with Devin Caughey)
5. "Mayoral Partisanship and Municipal Fiscal Policy." 2016. *Journal of Politics*. 78(4): 1124-1138. (with Justin de Benedictis-Kessner)
4. "Dynamic Estimation of Latent Opinion Using a Hierarchical Group-Level IRT Model." 2015. *Political Analysis*. 23(2): 197-211. (with Devin Caughey)
3. "Representation in Municipal Government." 2014. *American Political Science Review*. 108(3): 605-641. (with Chris Tausanovitch)
2. "Measuring Constituent Policy Preferences in Congress, State Legislatures and Cities." 2013. *Journal of Politics*. 75(2): 330-342. (with Chris Tausanovitch)

1. "How Should We Measure District-Level Public Opinion on Individual Issues?" 2012. *Journal of Politics*. 74(1): 203-219. (with Jonathan Rodden)

Editor Reviewed Articles in Journals and Law Reviews

3. "Public Opinion in Subnational Politics." 2019. *Journal of Politics*. 81(1): 352-363. Editor reviewed for Symposium on Subnational Policymaking. (with Devin Caughey)
2. "Spatial variation in messaging effects." 2018. *Nature Climate Change*. News & Views. April, 2018.
1. "Business as Usual? Analyzing the Doctrinal Development of Environmental Standing Doctrine since 1976." 2011. *Harvard Law and Policy Review*. Volume 5.2. (with Gregory Wannier).

Book Chapters

5. "Elections and Parties in Environmental Politics." 2020. *Handbook on U.S. Environmental Policy*. David Konisky, ed. (with Parrish Bergquist)
4. "Latent Constructs in Public Opinion." 2018. *Oxford Handbook on Polling and Polling Methods*. R. Michael Alvarez and Lonna Atkeson, ed. Oxford: Oxford University Press.
3. "The Application of Big Data in Surveys to the Study of Elections, Public Opinion, and Representation." 2016. *Data Analytics in Social Science, Government, and Industry*. R. Michael Alvarez, ed. Cambridge: Cambridge University Press.
2. "The Political Economy of Expropriation and Privatization in the Oil Sector." 2012. *Oil and Governance: State-Owned Enterprises and the World Energy Supply*. David G. Victor, David Hults, and Mark Thurber, eds. Cambridge: Cambridge University Press.
1. "Democratization and Countermajoritarian Institutions: The Role of Power and Constitutional Design In Self-Enforcing Democracy." 2012. *Comparative Constitutional Design*. Cambridge: Cambridge University Press. (with Susan Alberts and Barry R. Weingast).

Policy Reports

1. Reforming Baltimore's Mayoral Elections. 2020. Abell Foundation Report.
   `https://www.abell.org/publications/reforming-baltimores-mayoral-elections`

Unpublished Work

Book Project

"Dynamic Democracy: Citizens, Politicians, and Policymaking in the American States." Advance contract with University of Chicago Press. (with Devin Caughey)

Articles Under Review

"The Effect of Local COVID-19 Fatalities on Americans' Political Preferences." (with Lynn Vavreck and Ryan Baxter-King)

Works in Progress

"Electoral Accountability for Ideological Extremism in American Elections" (with Devin Caughey)

"Gerrymandering in Local Governments" (with Laura Royden)

"Moderates" (with Anthony Fowler, Seth Hill, Jeff Lewis, Chris Tausanovitch, Lynn Vavreck)

"Partisan Selection in California City Councils" (with Justin de Benedictis-Kessner and Dan Jones)

"The Effect of Television Advertising in United States Elections" (with John Sides and Lynn Vavreck)

"When Mass Opinion Goes to the Ballot Box: A National Assessment of State Level Issue Opinion and Ballot Initiative Results" (with Jonathan Robinson and John Sides)

"Inequalities in Participation, Voting, and Representation in Local Governments" (with Justin de Benedictis-Kessner and John Sides)

"Sexism and the Election of Female Candidates in American Elections" (with Alex Kurtz and Brian Schaffner)

"The Ideology of State Party Platforms " (with Justin Phillips and Gerald Gamm)

Non-Academic Writing

"How Local Covid Deaths Are Affecting Vote Choice." *New York Times*. July 28, 2020. (with Lynn Vavreck)

"A coronavirus recession would hurt all kinds of Republican candidates – not just Trump." *Washington Post*, Monkey Cage. March 18, 2020. (with Justin de Benedictis-Kessner).

"The Supreme Court is deciding a gerrymandering case. Here's the social science that the Justices need to know." *Washington Post*, Monkey Cage. June 1, 2019.

"New research shows just how badly a citizenship question would hurt the 2020 Census." *Washington Post*, Monkey Cage. April 22, 2019. (with Matt Barreto, Matthew A. Baum, Bryce J. Dietrich, Rebecca Goldstein, and Maya Sen)

"G.O.P. Senators Might Not Realize It, but Not One State Supports the Health Bill." *New York Times*. June 14, 2017. (with David Broockman)

Invited Talks

2019-2020: Princeton, UC Berkeley, University of Maryland

2018-2019: Stanford; Northeast Political Methodology Meeting at NYU; University of Maryland

2017-2018: USC PIPE Symposium on Studying Subnational Policy Making; BYU; University of Chicago Conference on Political Polarization

2016-2017: University of Virginia; UCLA

2015-2016: Washington University in St. Louis; Texas A&M; Arizona State University Conference on Campaigns, Elections and Representation

2014-2015: Yale; Columbia; Duke

2013-2014: Princeton; Boston University; Rochester University

2012-2013: MIT American Politics Conference; Columbia Representation Conference; Princeton Media & Politics Conference; Annual Meeting of the Society for Political Methodology

Grants

Russell Sage Foundation, 2019-2021 ($119,475)

GW UFF, 2019-2020 ($14,433)

MIT Elections Lab, 2019-2020 ($14,000)

Jeptha H. and Emily V. Wade Award, 2014-2016 ($59,686)

MIT Energy Institute (MITEI) Seed Grant, 2014-2016 ($137,147)

MIT SHASS Research Fund, 2012-2014 ($8,734)

Software

dgo: Dynamic Estimation of Group-Level Opinion. 2017. R package. `https://CRAN.R-project.org/package=dgo`. (with James Dunham and Devin Caughey)

Awards and Honors

OVPR Early Career Scholar at George Washington University, 2019.

APSA award for best journal article on State Politics & Policy in 2016.

Award for best paper on State Politics & Policy at the 2014 American Political Science Conference.

Graduate Fellowship, Dept. of Political Science, Stanford University, 2006-2012

David A. Wells Prize in Political Economy for Best Undergraduate Economics Thesis, Williams College, 2002

Phi Beta Kappa, Williams College, 2002

Teaching Experience

Instructor:

Measurement Models (Graduate-level) (GW), 2020

Political Representation (Graduate-level) (GW), 2019

Elections (GW), 2018, 2019

Multi-level and Panel Models (Graduate-level) (GW), 2017, 2018, 2019

Public Opinion (GW), 2017

American Political Institutions (Graduate-level) (MIT), 2014, 2016

Public Opinion and Elections (MIT), 2016

Energy Policy (MIT), 2013

Democracy in America (MIT), 2013, 2014

Constitutional Law & Judicial Politics (MIT), 2013, 2015

Making Public Policy (MIT), 2012, 2014

Teaching Assistant:

Introduction to American Law (Stanford University), 2010

Judicial Politics and Constitutional Law (Stanford University), 2009

Political Economy of Energy Policy (Stanford University), 2008

Introduction to International Relations (Stanford University), 2008

Introduction to Public Policy (Stanford University), 2007

Introduction to Econometrics (Williams College), 2002

Graduate Advising

George Washington University:

Alex Beck (Dissertation committee chair)

Colin Emrich (Dissertation committee member)

Jared Heern (Dissertation committee member)

Massachusetts Institute of Technology:

Leah Stokes (Graduated in 2015, Dissertation committee member)

Krista Loose (2016, Dissertation committee member)

Tom O'Grady (2017, Dissertation committee member)

Justin de Benedictis-Kessner (2017, Dissertation committee member)

Alex Copulsky (2017, Masters thesis committee member)

James Dunham (2018, Dissertation committee member)

Parrish Bergquist (2018, Dissertation committee member)

Meg Goldberg (2019, Dissertation committee member)

University Service

George Washington University:

Coordinator, Graduate Political Science Admissions Committee, 2019-2020

Coordinator, American Politics Workshop, 2018-2020

Member, Methods Exam Committee, 2017-2020

Member, Graduate Political Science Admissions Committee, 2018-2019

Massachusetts Institute of Technology:

Member, Energy Education Task Force, 2012-2017

Parking and Transit Committee, 2013-2017

Member, Graduate Political Science Admissions Committee, 2013-2015

Faculty Fellow, Burchard Scholars, 2013-2015

Stanford University (as graduate student):

President, Stanford Environmental Law Society, 2009-2010

Executive Board Member, Stanford Environmental Law Society 2008-2010

Member, University Committee on Graduate Studies, 2007-2009

Member, University Library Committee, 2007-2008

President, Political Science Graduate Students Association, 2007-2008

Professional Service

Reviewer: American Political Science Review, American Journal of Political Science, Journal of Politics, Political Analysis, Political Behavior, Econometrica, Quarterly Journal of Political Science, Legislative Studies Quarterly, Political Research Quarterly, American Politics Research, British Journal of Political Science, Journal of Law and Courts, Public Opinion Quarterly, Political Science Research and Methods, State Politics and Policy Quarterly, Journal of Experimental Political Science, Nature Climate Change, Urban Affairs Review, Journal of Health Politics, Policy and Law, Perspectives on Politics, Cambridge University Press

Member, Program Committee, Midwest Political Science Association Conference, 2020

Lead Organizer, Local Political Economy APSA Pre-Conference at George Washington University, 2019

Member, Planning Committee, Cooperative Congressional Election Study (CCES), 2018

Member, Best Paper Committee, State Politics Section of the American Political Science Assoc., 2018

Editorial Board, Journal of Politics, 2017-18

Executive Committee, Urban Politics Section of the American Political Science Association, 2015-2017

Organizing Committee, Conference on Ideal Point Models at MIT, http://idealpoint.tahk.us, 2015

Member, Best Paper Committee, Urban Politics Section of the American Political Science Assoc., 2015

Consulting

Consultant, *Abell Foundation*, Report on Potential Institutional Reforms for Baltimore's City Elections

Expert, *League of Women Voters of Pennsylvania* v. *the Commonwealth of Pennsylvania*, Partisan Gerrymandering Case (2017-18)

Expert, *League of Women Voters of Michigan* v. *Johnson*, Partisan Gerrymandering Case (2018-2019)

Expert, *New York Immigration Coalition* v. *US Dept of Commerce* & *State of NY* v. *US Dept of Commerce*, Effects of Undercount on Census due to Citizenship Question (2018)

Expert, *APRI et al.* v. *v. Smith et al.*, Partisan Gerrymandering Case (2018-2019)

Community Service

Sierra Club: National Board of Directors (2009-2015)

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